Politecnico di Milano
SCHOOL OF INDUSTRIAL AND INFORMATION ENGINEERING
Master of Science – Energy Engineering

WORK FROM HOME

THE IMPACTS OF SMART WORKING ON FUTURE GLOBAL ENERGY CONSUMPTIONS IN BUILDINGS

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Academic Year 2020 – 2021

Acknowledgements

I would like to first thank Prof. Massimo Tavoni for the given opportunity of working in a prestigious research environment and for the guidelines he offered me throughout the elaboration of this thesis. I am grateful to my Co-Supervisor Dr. Giacomo Marangoni for the help and the time we spent in these six months, trying to define methods of research able to grasp the dynamics of the ongoing mass-scale WFH phenomena. I also thank Massimo Sbardelaro, owner of "Vecomp s.p.a", for the information about his actual and historical building energy consumptions he shared me and Dr. David Sykes - Head of Data Science of Octopus Energy - for the gentle reply to my request for more information.

Sommario

Un terzo dei consumi finali mondiali di energia è dovuto al settore delle costruzioni. Sono quindi molti gli studi e sforzi volti ad incrementare i livelli generali di efficienza energetica del settore e a limitarne le relative emissioni. Cosa comporterebbe tuttavia un cambio strutturale dei profili di utilizzo degli edifici, residenziali e commerciali, nei prossimi decenni? Il settore vedrà un aumento o riduzione netta dei consumi? L'attuale pandemia da COVID19 ha costretto miliardi di persone a casa, ad Aprile 2020 nel suo apice il 50% della popolazione mondiale si trovava confinata. Il lavoro remoto, o Work From Home (WFH), è stato largamente adottato e favorito dai governi di tutto il mondo. In molti paesi OECD i livelli di telelavoro sono improvvisamente cresciuti dal 10% pre crisi a soglie del 45% della popolazione lavorativa in poche settimane. Come conseguenza dei cresciuti livelli di occupazione degli edifici, i consumi residenziali sono cresciuti in tutto il mondo. Al contrario, la progressiva chiusura delle attività commerciali e degli edifici pubblici ha causato una riduzione dei relativi consumi. Questa ricerca si avvantaggia dell'esperimento naturale del COVID19 per indagare il futuro del settore delle costruzioni in scenari di WFH. Abbiamo utilizzato dati raccolti in tutto il mondo durante i primi mesi del 2020, cercando di individuare patterns significativi. L'analisi empirica ha permesso di estendere ed integrare il modello energetico globale per il settore delle costruzioni EDGE. Nello specifico, in questa tesi abbiamo migliorato il modello EDGE e sviluppato un inedito scenario di Work From Home, assumendo livelli sostenuti e strutturati di smart working nei prossimi decenni. Abbiamo poi elaborato gli impatti del WFH sui consumi energetici settoriali. I risultati mostrano variazioni nette tendenti globalmente a zero, a causa di effetti di compensazione tra settore residenziale e commerciale e tra paesi in via di sviluppo e sviluppati. Il modello indica variazioni nette intorno al -1% nel 2050, ma con grandi differenze tra regioni e con incrementi per il settore residenziale tra il 2 e il 5% e decrementi per quello commerciale intorno all'8%. Questa analisi può favorire quindi la comprensione della futura domanda di energia del settore delle costruzioni.

Parole chiave: Work From Home, Building Sector, Smart Meter, COVID19

Abstract

Around one third of world final energy use is in the Building Sector. It has been therefore object of extensive research aimed at improving efficiency and reducing sector emissions. But what if structural changes in the way people live and work in buildings will take place in the next decades? Will the sector experience increasing or decreasing consumption trends? The ongoing COVID19 pandemic forced billions of people at home, roughly 50% of world population at its peak. Working from Home (WFH) has become widely adopted and encouraged by governments all over the world. In most of OECD countries WFH penetration suddenly went from levels well below 10% to peaks of 45% of total working population. As consequence of higher occupancy levels, residential consumption rose all over the world. By contrast, the progressive closure of commercial activities and only partial occupation of offices and publics buildings allowed for decrease of energy consumption. This research work aims at taking advantage of the natural experiment of COVID19 to understand the future of the building sector under smart work. We exploit data collected for the building sector from March 2020, with the purpose of extracting useful patterns. The empirical analysis is used to extend and integrate the EDGE global building model. Specifically, in this thesis we have improved the EDGE model and developed a novel Working From Home Scenario, assuming sustained and projected reliance on smart working in the next decades. We work out the impact of WFH on total sectoral energy consumption. Results indicate that the energy demand impact of WFH is close to zero, due to the compensating effect of increased residential consumptions and reduced commercial ones, and to disparities between developed and developing regions. Model outputs show net reductions centered around -1% for 2050, but with great variations across regions and net increases for the residential sector of about 2 to 5% and decreases for the commercial of about 8%. This analysis can help inform the future of building energy demand.

Keywords: Work From Home, Building Sector, Smart Meters, COVID19.

Extended Abstract

Scope of the work

The main objective of this research was to establish to what extent scenarios of extensive Work from Home (WFH) could affect future energy consumption patterns and relative emissions of the Building Sector.

The study was inspired by the ongoing Covid 19 pandemic. Most of the data and of consulted literature was therefore produced after March 2020. The idea was to make advantage of this unprecedent amount of data to explore correlations between WFH and energy consumption, finding patterns to project possible future scenarios in which WFH begins being structurally adopted. [1, 2] The strict measures imposed by world governments in attempt to slow down the contagious curve forced billions of people at home. Industries and offices were closed, and work from home began being massively adopted to secure business continuity. [3] The increased number of people staying at home, translated in higher levels of residential building occupancy, and led to an increase in energy consumption. By contrast, the reduced presence of personal in offices resulted in a net decrease of energy consumed by the commercial building sector. [4, 5]

A vast majority of collected data reported however “raw” energy consumption variations for residential and commercial building sectors. Possible correlations with WFH penetration levels, as reported during Covid 19 pandemic, were initially hidden, due to a simple constatation. Confined population cohort included both workers and the rest of population. The same occurred for the commercial sector, forced closures affected not only “teleworkable” sub sectors but also those normally not subjectable to WFH, as food retail shops.

Methodology

EDGE Building Energy Demand GEnerator Model was chosen as modelling platform. It was originally developed by the Potsdam Institute for Climate Impact Research, and subsequently refined at Politecnico di Milano. In a thesis work of R.Davide (2018) was investigated the role of building policies for long term efficiency, and upgraded the computation of U-Values in the model. EDGE is a bottom-up, statistically-based simulation model, which is multi-regional and allows for long term projections. The model projects buildings energy demand across 11 regions and 5 end-uses. [6] In this work the fundamental structure of the model was maintained; updates were made to enhance EDGE with the new correlations and variables needed for a WFH implementation. Nine principal variables were added and the model was upgraded to provide energy insights also for the commercial sector. First was identified the number of home workers around the world (WFH level) according to the narratives of 5 different SSP scenarios, and then modeled its evolution in the future with different methods. Then, correlations were established between WFH levels and energy consumption variations for Residential and Commercial sectors.

Work From Home

There have been many attempts to measure the percentage of workers that fully operated from home during the pandemic. Dingel-Neiman [7] and International Labour Organization [3] provided a comprehensive review of those methods along with a methodology to calculate the work from home potential of countries in the world. The method adopted by Dingel Neiman used occupational descriptions from the Occupational Information Network (O*NET) to estimate the probability for an occupation to be done remotely. To produce estimates for other countries than US a similar use of the US O*NET surveys was done for the International standard classification of occupations (ISCO). Final results showed a clear positive relation between GDP per capita and the shares of job that can be done from home, as was also confirmed by a World Bank study. [8]

International Energy Agency estimates, basing on Dingel-Neiman and ILO works, that around 20% of jobs globally could be done from home, with values ranging from 10% in Sub Saharian Africa to 45% in wealth EU countries. IEA also confirms the positive correlation between WFH potential and GDP cap. [9] To transform an extensive variable, the share of teleworkable jobs from Dingel Neiman, into an intensive one, the number of home workers, and make it projectable, “ETPr” Employment to Population Ratios were included. ETPr show the percentage of working age population, aged 15 to 65, actually employed. Once obtained the number of workers for a certain geographical region in a year, we derived the number of Home Workers by multiplying with Dingel Neiman coefficients. ETPr were provided by World Bank while population projections by IIASA’s World Population Program [10]. The two datasets were matched to produce as output five different SSP Shared Socioeconomic Pathways Work From Home penetration scenarios. Another method adopted consisted in an “upgrade” of the Dingel Neiman method, done by adding more variables to the WFH interpolation. The exploitation of the full potentials of the IIASA dataset allowed for a WFH calibration based also on educational and age profiles, following the recent evidences from World Bank. As modeled in this study, Work From Home depends therefore from GDP per capita, higher values leading to higher overall teleworkability, and from population composition and macro Labour Market structures.

Energy Consumption Variations

Data were collected for variations of both Energy Carriers and of End Uses. EDGE’s architecture operates by defining five “Useful energy demands”; Cooking, Water Heating, Space Cooling, Space Heating and Appliances and Lighting. They depend on Socio-economic and climatic drivers such as Income, Population, Pop Density,

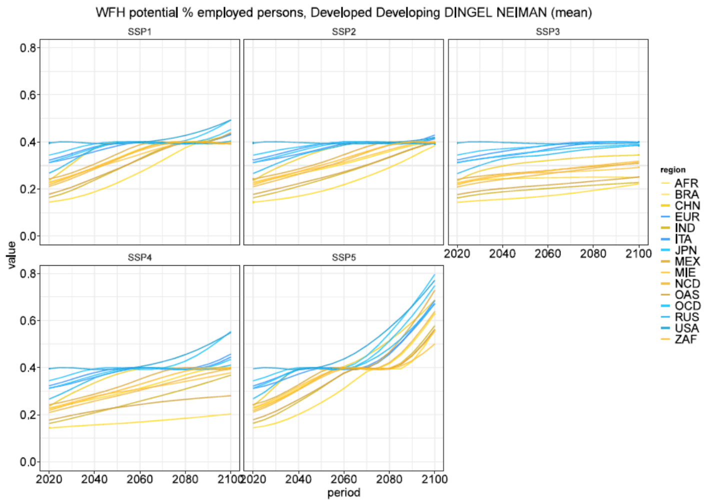


Figure 1. WFH modeled from Dingel Neiman correlation

Cold Degree Days and Hot Degree Days. Those drivers were kept unaltered. Instead, changes were necessary for the End Use generating functions. The assumption is that Work From Home alters only End Use demands and not the underlying Energy Carrier mix. For the Residential Sector it was possible to identify specific WFH variations for each End Use, not so for the Commercial Sector.

By applying both End Use and Energy Carriers variations to an End Use-Energy Carrier Matrix consistency was checked. This was necessary as reported increases in End Use consumptions were mostly obtained by surveying or simulations, while Energy Carriers variations were more trustworthy because reported by energy providers themselves.

Energy Carriers Residential Variations

As anticipated, most of literature did not consider explicitly working from home during COVID19 pandemic, energy consumption variations were reported as consequences of confined population staying at home. [4, 11] Still, in order to assess general order of magnitudes of WFH deltas, the relevance of these studies was high for the purpose of the research.

However, to develop accurate WFH scenarios, data were needed for increases of energy consumption specific per home worker. One study, made by Octopus Energy, a British Energy Provider, tried to answer that question by analyzing domestic electricity and gas consumption profiles of 115’000 of its clients, through access of their smart meters [12] . Two weeks were considered, before and after the Shelter in Place (SIP) national order of 16 March 2020. Octopus found 30% of its clients on WFH with specific electricity increases per home worker ranging from 13% to 30% (1-2 KWh), and gas increases of 20%.

The approach chosen by Octopus Energy was tested and reproduced on a sample of 1230 clients of a large scale multi-utility group-Italy and restricted on Electricity uses only. The two work weeks considered were the one from 24 to 28 February 2020

(Week1) and the one from 16 to 20 March 2020 (Week2). Italian Shelter In Place order was effective the 8th of March. [13] Temperature differences between the first and second week were on average of about 1°C. The signal, having a daily hour resolution, was then adjusted to isolate the increase due only to clients performing home working. First, observing window was limited to hours from 9am to 5pm (working hours), then consumption profiles were binned, and two cumulative distribution curves were obtained, one for the week pre-lockdown and another with it in place.

P was defined as the percentage of clients working from home and Q their increased electricity consumption. These parameters, applied to the Week1 distribution curve, were varied so to minimize the Kullback Leibler divergence between the newly generated distribution curve and the Week2 one. The optimum is to be found with 2 parameters constrained Lagrangian optimization methods and results showed similarity with Octopus findings. Around 20% of clients were estimated being in WFH with specific increases in electricity consumption ranging from 1 to 2 KWh, equal to about 15%. Another method adopted instead pointed to higher increases in consumption, between 25 to about 35%.

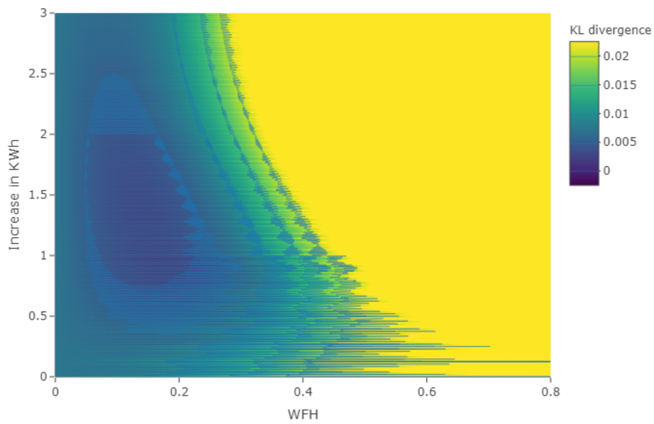


Figure 2. RES: KL, 100'000 simulations, from 1215 clients

End Uses Residential Variations

16 different data points were found from an extensive literature review and used for the calibration. As anticipated before, most of papers retrieved data for increments in End Use demands due to Shelter in Place orders basing on surveys or simulations. The importance of a validation through Energy Carriers was therefore crucial. Finding specific increments per home worker was not possible, and less needful. In fact, variations were most of the cases already framed as increments in frequency of activity, eg. 50% more Cooking meant adding around a meal a day. Apart from Cooking, which increments varied from a +35% (Australia) to +100% (Serbia) all other End Uses showed concordance and acceptable variance throughout papers.

Validation Matrix

The validation of increments was performed on UK, after retrieving its End Use-Energy Carrier Residential Matrix from Eurostat [14], where the i-rows represent 5 End Uses and j-columns 5 Energy Carrier. The choice of UK as calibrating country was due to the unique availability of both specific Electricity and Gas WFH increments. Moreover, the presence of disturbing signals coming from possible undetected increments in other energy carriers could easily be excluded. Gas and Electricity in UK are in fact by far the most used energy carriers, Gas 63% and Elec 24%. Space and Water heating account for 80% of residential energy consumption (63% SH and 15% WH) and are provided around 80% by gas (75% SH and 85% WH). Applying a delta of +22% for Electricity and +20% for Gas and the vector of average End Use increments found from literature, errors were reduced to 1%. Overall the calibration showed stability from perturbances.

Commercial Reduction

Finding accurate data for reported decrease in consumption due to enforced lockdowns was not an easy task. The magnitude of deltas varied a lot in relation to local restricting measures concerning commercial sectors. Some countries did not implement strict WFH programs, others did not order the closure of most of commercial activities (as Australia) and therefore an overall signal interpretation was not possible. As done for the Residential sector, a general literature overview was nevertheless accomplished, to define lower and maximum ranges. 19 Data points were in total collected.

The search for data was then restricted to papers providing analytics for commercial subsectors related mostly to Real Estate and Public, the main sectors of interest for a WFH scenario. The choice of six data points allowed the calibration of a curve of "Energy Reduction" (mostly Electricity) as function of WFH potential. The correlation is linear with intercept in 0. An office WFH level of 80% pointed to average energy savings of only 20%. Such low saving performances occurred mostly because buildings' HVAC systems, Elevators, Emergency Lights etc. still must function even if no personal is physically on site. [15] Of great contribution were three data points provided by a simulation performed by researchers at Dalarna University (Sweden) of a District in Sweden (2020), aimed at understanding the impact of different lockdowns levels (and therefore WFH potential) on Residential and Commercial local consumption patterns. [16] Another data point came from own retrieved Electricity Bills (4 years data) of an Office building located in Verona (Italy) hosting 80 workers. Monthly consumption data were provided along with registered WFH levels, which reached a peak of 70% in April 2020 and an associated Electricity reduction of 27%.

Most of literature highlighted the need of buildings adjustments to account for structural higher levels of WFH. With such efficiency improvements, eg. less energy intensive HVAC water circulating systems or zoning of lighting, expectations were of energy reductions of at least 50% for WFH levels of 80% or more. [17, 18] These considerations allowed for the construction of a "future" commercial sector energy reduction curve, function of WFH potential. Data were available and collected only for Electricity and modeled in EDGE as a uniform reduction across all End Uses.

Given the strong prevalence of Electricity as Energy Carrier in the commercial sector, such forced approximation was considered acceptable.

Commercial Residential Separation

The EDGE model combines Residential and Commercial demands; End Use functions are dependent on Floor Space, which is projected separately for the two sectors but then summed before serving as input for End Use equations. I split the demand by retrieving IEA data from ETP 2017. [19] Data were available for 12 World regions, that mostly overlapped with EDGE ones. They originally extended to 2060 and were projected through a Damped Holt's method up to 2100. Commercial energy reductions coefficients had to be multiplied by the total amount of Commercial Energy related to WFH. In fact, subsectors like Food, Retailing or Lodging had very low WFH levels and their relative sectorial energy consumptions were not accounted. The calibration was made first on US and then on EU, India, Singapore and Australia, returning shares ranging from 40% to 50%. For US energy consumption data were collected from the EIA database [20] and then combined with respective WFH sub sectorial shares as found by Dingel-Neiman. As first approximation the binding method was based upon the definition of a threshold level of WFH, equal 14%, greater which its sub sectorial energy was included. A second method instead went through the analysis of the World Input Output Matrix (WIOD) modified by the European Commission Joint Research Center to account for energy cross sectorial flows (NAMEA matrix). [21] Results obtained with NAMEA confirmed trends observed with the first method.

Main Results and Conclusions

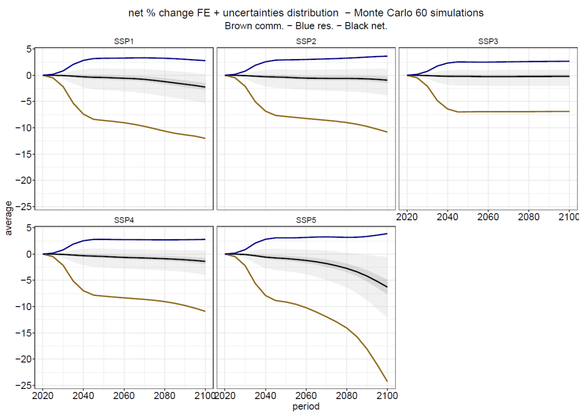
A Monte Carlo simulation was performed to account for the variability of the nine principal parameters given as input to the model. The probability profiles were normal distribution centered around the average of deltas found from literature and own research. Commercial reduction curve had assigned a probability distribution centered in a "medium energy savings" scenario, with a low case scenario equivalent to the linear curve registered during COVID19 pandemic and a best case scenario as prospected in case of structural higher levels of WFH. A sensitivity analysis performed on the variables showed that 4 out of 9 parameters influenced most model output, in particular, coefficients related to WFH levels and to commercial reduction curves. Including as extra variable the set of coefficients for commercial and residential separation it was found to be, by far, the most influencing parameter affecting model output. Due to their strong disturbances in output induced by even small variations (as max. linear identity magnification) they were not included in the Monte Carlo simulation.

Across all 5 SSP scenarios, net variations due to Work From Home are projected to be slightly negative by 2050, with more pronounced trends by the end of the century. In all scenarios residential final energy is expected to increase by 2050 from 2% to 5%, while commercial final energy to decrease of around 8%, with the greatest reductions prospected in a SSP5 scenario, particularly if extended up to 2100. WFH should therefore impact globally, at net near zero (-2%) by 2050, considering building sector as a whole, due to the compensation effect between commercial and residential sector (in line with available literature). Analyzing however regional variations strong differences appears in magnitude of changes, between developing and developed countries. Results indicates that global net zero is also reached through a compensation between their relative variations. In all scenario, particularly in the SSP4 "Inequality" and in SSP3 "Regional Rivalry" developing countries show net variations near zero or slightly positive, while developed countries are denoted by net reductions of around 3% by 2050. This trend is mostly caused by the higher shares of Residential End Use in Developing countries, due to lower commercial penetration and climatic differences.

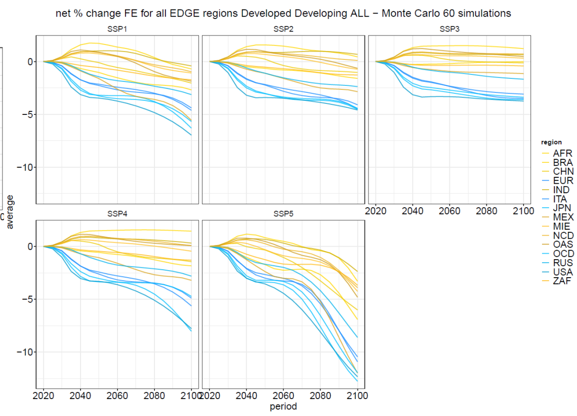
A breakdown of Deltas by End Use and Energy Carrier highlights the net positive contribution of Cooking and the strong negative one of Appliances and Lighting. The former due to its unique presence in the Residential Sector while the latter due to its prevalence in the Commercial sector. Space Cooling share in the residential sector is projected to increase constantly throughout the century in developing countries, and therefore its contribution span between slightly negative to positive values from around the 50's.

Lastly, we considered an extreme case of a global Lockdown COVID19 scenario. Results showed reductions for the commercial sector of around 20% and increases in residential sector of around 10%, leading to a net increase of final energy required by the building sector of 0 to 5%. These numbers are comparable with the ones obtained by two studies (Nature Climate Change-2020 [4, 11]), that indicated commercial reduction in emissions of 20 to 50% and residential increases of 10 to 20%. This provides confirmation of the accuracy of the calibration.

Overall, these results provide insights for thinking about future scenarios of energy demand in the building sector which account for change of habits and technology. A natural extension of the work should include the transportation sector. Although transport is not included in EDGE it could contribute to significant energy and emission reductions as commuting is reduced due to WFH. IEA estimates avoided CO2 emissions due to less commuting being 3.6 times greater than those incremented in the residential sector. [9] If this contribution was to be artificially included in the model, net savings could reach 4 to 5% by 2050.



(a) Res. Comm. Net deltas %



(b) Regional differences

Figure 3. Final Energy variations

Acronyms

2DS	Two Degrees Scenario
AFR	Africa
AL	Appliances and Lighting
AMI	Advanced Metering Infrastructure
AR5	Fifth Assessment Report
ASEAN	Association of Southeast Asian Nations
B2DS	Beyond Two Degrees Scenario
BBC	British Broadcasting Company
BCA	Building and Construction Authority
BEBR	Building Energy Benchmarking Report
BLS	Bureau of Labor Statistics
BRA	Brazil
C.F.T.C	Commodity Futures Trading Commissions
CBECS	Commercial Building Energy Consumption Survey
CC	Climate Change
CDD	Cold Degree Days
CK	Cooking
CNBC	Consumer News and Business Channel
DN	Dingel Neiman
DOD	Department of Defence
DPCM	Decree of the President of the Council of Ministers
EC	Energy Carrier
EDGE	Energy Building Demand Generator
EIA	Energy Information Administration
ENEA	Ente per le nuove tecnologie, l'energia e l'ambiente
ETPr	Employment to Population Ratio
EU	European Union
EUR	European Union
F2F	Face to face
FC	Final Consumption
FED	Final Energy Demand
GAM	General Additive Model
GCV	Generalized cross Validation criterion
GDP	Gross Domestic Product
GEA	Global Energy Assessment
GHG	Greenhouse Gas Emissions
GNI	Gross National Income

GWA	Generalized Work Activities Questionnaire
HDD	Hot Degree Days
HVAC	Heating, ventilation, and air conditioning
IAM	Integrated Assessment Model
ICT	Information and Communications Technology
IEA	International Energy Organization
IIASA	International Institute for Applied Systems Analysis
ILO	International Labor Organization
IND	India
IPCC	Intergovernmental Panel on Climate Change
ISCO	International Standard Classification of Occupations
ITA	Italy
JCT	Job Characteristic Theory
JPN	Japan
JRC	European Commission Joint Research Centre
KL	Kullback Leibler
LMPS	Labor Market Panel Surveys
MEX	Mexico
MIE	Middle East
MIT	Massachusetts Institute of Technology
NAMEA	National Accounting Matrix including Environmental Accounts
NBER	National Bureau of Economic Research
NCD	Other non OECD
NDC	Nationally determined contributions
O*NET	Occupational Information Network
OAS	Other South and Asia
OCD	Other OECD
OECD	Organisation for Economic Co-operation and Development
OES	Occupational Employment Statistics
OLADE	Latin America Energy Organization
PIAAC	Program for the International Assessment of Adult Competencies
PIK	Potsdam Institut für Klimafolgenforschung
REMIND	REgional Model of Investment and Development
RMSE	Root Mean Square Error
RPC	Representative Concentration Pathway
RSE	Research on the Energy System
RTS	Reference Technology Scenario
RUS	Russia
SC	Space Cooling
SD	Standard Deviation
SH	Space Heating
SIP	Shelter in Place
SOC	Standard Occupational Classification
SRES	Special Report on Emissions Scenarios
SSP	Shared Socioeconomic Pathways
STEP	Skills Towards Employability and Productivity
UMI	Urban Modeling Interface

UNFCCC	United Nations Framework Convention on Climate Change
US	United States
USA	United States
WCQ	World Context Questionnaire
WFH	Work From Home
WH	Water Heating
WIOD	World Input Output Matrix
WISERD	Wales Institute of Social and Economic Research
WP	Working Population
ZAF	South Africa

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Chapter 1

Introduction and Motivation

"No challenge poses a greater threat to future generations than climate change."
United States President Barack Obama

1.1 General Context

Climate Change constitutes one of the biggest challenges humanity has ever faced. In recent years, all major international forums saw it included in their agendas. It has become subject of strong political discussions and motive of action for millions of young students all around the world.

Most importantly, finance investments founds and corporations have begun to reduce constantly their exposure toward fossil fuels, switching to greener portfolio partially or totally. Climate Change is now a matter of National Security [22] and existential level threat for many insurance firms and economic actors. [23] In 2019 US Pentagon reported in a document [24] , detailing risks for US world strategic assets: "The effects of a changing climate are a national security issue with potential impacts to missions, operational plans and installations, DOD must be able to adapt current and future operations to address the impacts of a wide variety of threats and conditions, to include those from weather, climate, and natural events." In September 2020, for the first time a US Federal market regulatory agency, the C.F.T.C (Commodity Futures Trading Commissions) concluded in a report [25], initiated by the Trump administration, that "A world wracked by frequent and devastating shocks from climate change cannot sustain the fundamental conditions supporting our financial system."

Scientific community is therefore increasingly asked by governments and institutions to address Climate Change mitigation and adaptation issues. United Nations Intergovernmental Panel on Climate Change (IPCC) was established in 1988 and has so far produced five assessment report that constituted scientific basis for political resolutions at United Nations Framework Convention on Climate Change (UNFCCC). IPCC has currently 195 members from all over the world but thousands of researchers contribute to its reports, the last one being currently prepared and expected for release in 2022. IPCC reports do not constitute original research per se, their purpose is to make extensive and methodologically accurate reviews of published literature, and to interface with policymakers by including a special summary reports which goes through a review and approval of delegates of more than 120 countries.

IPCC fifth Assessment Report AR5 [26] included critical contributions for UNFCCC's Paris Agreement 2015, an international climatic and economic treaty that set ambitious goals such as limiting global average temperature well below 2°C above pre-industrial levels. IPCC highlighted the advantages of pursuing efforts not to surpass a 1.5°C limit, for world ecosystems, human development and the containment of natural hazards. Humanity is estimated to already having caused an increase of 1°C above pre-industrial levels and it is currently depleting its carbon budget at a rate of about 42 GtCO2 per year. Remaining carbon budget in 2020 to not exceed a 1.5°C warming with a probability of between 66 to 33% is estimated to be of 230-440GtCO2, which is equivalent to between six and 11 years of global emissions at current rates. [27, 28]

The most relevant sources of greenhouse gases emissions are related to agriculture and land-use, industry, transport and buildings. Analysis of global carbon cycle for 2019 show that between 33-37 Gt CO2/yr are emitted from fossil fuel industry, while land-use change (deforestation) are responsible for an additional release of 3-8 Gt CO2/yr. CO2 sinks are instead related to the atmosphere, which keeps 44% (18 Gt CO2/yr) of these emissions, while oceans absorb 22% (7-11 Gt CO2/yr) and a remaining 33% (9-14 Gt CO2/yr) is absorbed by the Earth biosphere. Global fossil CO2 emissions have risen steadily over the last decades and had shown no sign of decline until the world spreading of COVID19 pandemic in 2020. [26]

Temporary reduction in emissions registered during COVID19 pandemic of about 7% are indeed in line with the required rate of decrease. However, rather than casting lights of optimism these data unveil the extent in magnitude of structural changes needed to stay successfully below IPCC's indicated thresholds. Moreover, history shows the recurrence of energy intensive recovery plans that are often deployed as economic stimulus after big-scale crisis events. More than ever now are required economic recovery efforts targeted to drive emissions down, mainly through the financing of high potential green investments. [29]

Reality is that chances of limiting temperature increase of 1.5°C are so low that projections are of already exceeding the threshold within 10 years, with a central estimate of between 2030 and 2032 [27], if emissions are not rapidly reduced, and to exceed the threshold of 2°C in 30 years, in a scenario of modest mitigation, as prospected in the latest IEA World Energy Outlook.

The dangers the world is facing from exceeding the threshold levels indicated by IPCC are mostly due to the high sensitivity of physical systems to temperature increases. Some cascade effects and tipping points can consequence in extreme impacts and yet their activation mechanisms are still not well understood. They are simply "too risky to bet against". [30] These eventualities should justify the variety of economic efforts and policies needed to reduce emissions as much as the state of art of technology allows.

What makes so demanding the task of reducing emissions at the required extents in such a short time is the complexity of the process as a whole. Technologies are often available and in place, but strong inertia in sectorial conversions, low political

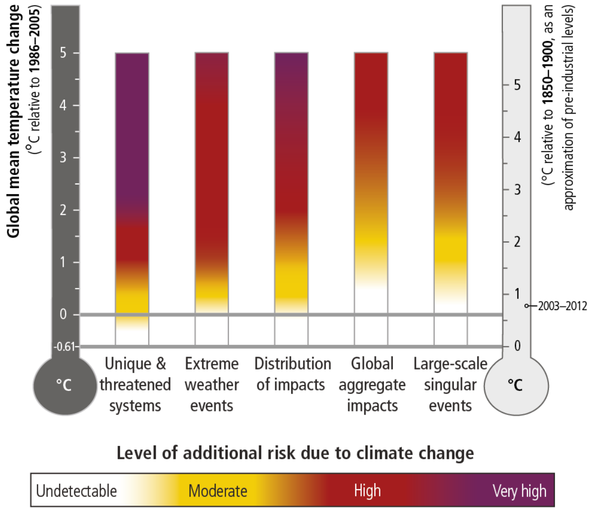


Figure 1.1. Non linearity of climate risks, IPCC SR15

consensus and rivalries between world regions have often dumped, halted or reversed green economy conversions. A well-known behavior that makes most of climatic treaty so ineffective is the one of “free riding”, as stressed by W.Nordhaus (Nobel Prize in Economic 2018), who address it as principal cause of failure in setting effective carbon taxes over the world. [31]

The reduction of GHG emissions requires acting simultaneously on many sectors, one of prioritizing criteria is their contribution to total emissions. Energy related emissions accounted in 2016 for 73% of global GHGs. Singular biggest contributors were Industry sector with a share of 24%, Building sector with a share of 18% and Transport with a share of 16%. In Building sector a breakdown between Commercial and Residential sector see the former responsible for 40% of Building emissions and the latter for the remaining 60% (2016). With a focus on Energy and Process related emissions IEA 2019 World Energy Statistics and Balances identifies Building and Construction sector as first contributor in 2018 with a share of 39% of energy emissions and of 36% of final energy use. Industry sector comes second with a share of 31% of total energy emissions and 32% of final energy and last is Transport sector with a share of 23% of energy emissions and 28% of final energy consumption. [32]

However, as highlighted in recent IEA World Energy Outlooks, the path for a Sustainable Development Scenario and even more for a Net Zero Emissions by 2050 scenario, needs a strong implementation of many efficiency measures across all sectors, that are projected to contribute in total for about 44% of cumulative CO2 emissions savings. It is therefore important to adequately characterize and study in details each of these efficiency improvements, despite their fractional modest contributions. [32–35]

1.1.1 The Building Sector

Decarbonization of the Building sector is critical to achieve the ambitious goals agreed by world national delegations at the Paris Agreement of 2015. Overall (including embodied emissions) the sector contributes to almost 40% of energy related emissions, and improvements could contribute to mitigation goals in a cost effective way. According to most models the savings in energy costs typically more than exceed the investment costs. [36, 37]. IIASA GEA Global Energy Assessment assess that if today's best practices in construction were deployed cumulative energy savings would near triple in economic value the costs of realization. [38]

IEA identifies as most important actions needed to decarbonize the sector:

- Switching to renewable energy sources
- Improving building design, while increasing thermal comfort
- Increase the efficiency of heating, cooling, ventilation systems and of appliances and equipment.

Up to now however, registered emissions trends for the sector show persistent increments. Final energy demand in buildings in 2018 rose of 1% from 2017, average increases being of around 1%/yr, with a first time increase below 1% in 2019 due mostly to milder weather. These increases sharply contradicts world goals of 7,6%/yr emissions reductions, needed to not exceed a 1.5°C warming. Moreover the rate of improvement in sectorial energy intensity has also slowed down, reduced to half the average of the previous year from 2010. [39]

In 2018 a total of 136 countries mentioned buildings in their Nationally Determined Contributions (NDC), that were due to revision in 2020. The importance of the sector to tackle Climate Change and even foster national economies through incentives for building renovation was recognized. Yet their NDC lacked specific descriptions on how to decarbonize the sector and reverse the positive emissions trends.

Building stock is set to double by 2050, with some studies pointing to increases in floor area of over 150% by half of the century, but this increase is not necessarily related to an increase in final energy consumption; according to GEA "efficiency" pathway heating and cooling energy uses could decrease of about 50% compared to actual level by 2050 if all energy savings measures were deployed. In a scenario where no energy savings policies are deployed, forecasts see increases in consumption of about 75% compared to 2010 levels, with some models projecting increases of over 150%. It is therefore clear the importance and urgency of adequate policies and regulations for the expanding building sector.

The 8% net increase in final energy demand that the sector has experienced over the past ten years is mostly due to an increase in floor area/occupancy (+12%) and population/building use (+4%). In the residential sector around 57% of energy demand came in 2018 from heating and cooling, it is projected to increase of around 180% by 2050 in a scenario of frozen efficiency. Appliances had a share of 20%, Water Heating of 16% and the remaining 7% was consumed for Cooking and Lighting. [36]

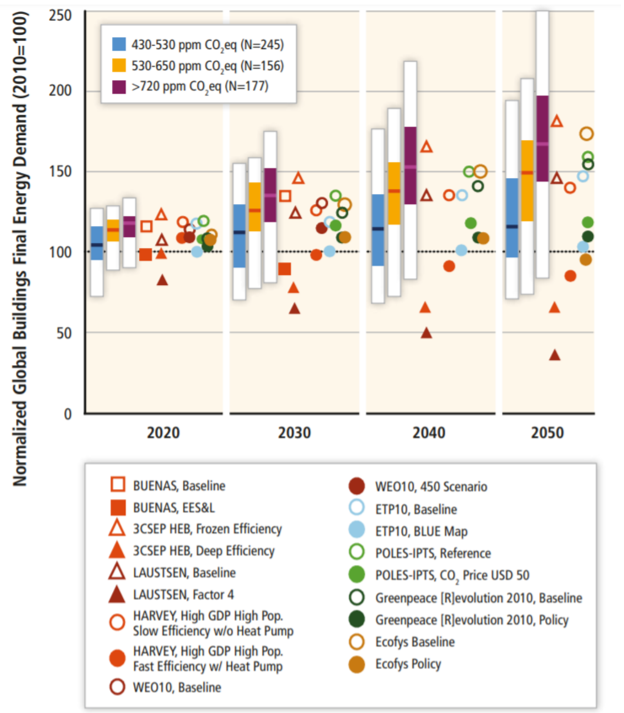


Figure 1.2. Building Final Energy Demand projections, IPCC AR5-Ch.9

1.2 Research Question

"Covid 19 Pandemic, a mass experiment for the climate"
(BBC-Climate Change 25 June 2020)

Humanity is currently facing one of the biggest challenges from the end of World War Two. The ongoing COVID19 pandemic, declared by World Health Organization on 11 March 2020, has already caused, one exact year after, the death of over 2.5 Millions people and the greatest recession the world had ever experienced from the Great Depression of 1929. First quarterly GDP variations of 2020 indicated an astonishing world average of -17%. [40]

To contain the spread of the virus world governments had to put in place unprecedented restrictions on travel and work. Google mobility trends indicate that in April more than 80% of the world population, 4 billion peoples, reduced their travel by more than 50%. At its peak, on 3 April 2020, 90 countries had already called for confinement of half of humanity. More than 3.9 billion people were confined at home. Correspondingly, the fraction of global CO2 emissions produced in areas subjected to confinement reached 89%. The 7 of April 2020 was estimated having the highest daily change in CO2 emissions for the period from 1 January to 30 April 2020; in fact emissions decreased that day of 17% (-11 to -25%) and reached their homologous levels of 2006. [4]

Some countries reached maximum daily decreases of about 26%. Confinement orders thereby drastically altered patterns of energy consumptions, proportionally to the severity of country's lockdowns. [41]

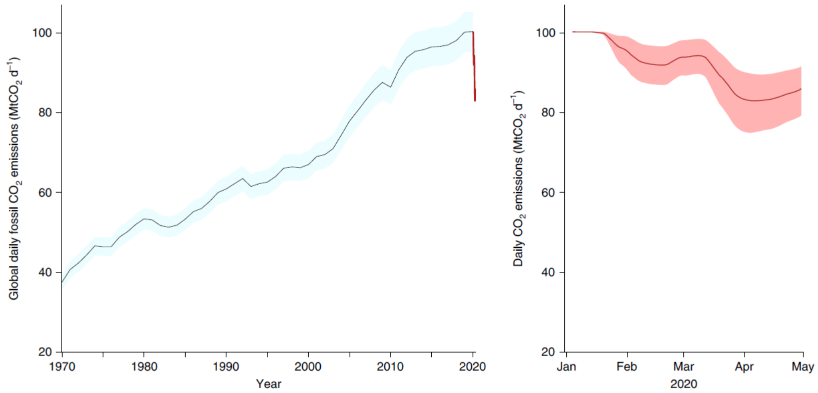


Figure 1.3. Emission reductions due to first lockdowns, Le Quéré et al.

Some studies [11] tried to measure changes in "activities" and emissions of various sectors as function of the confinement levels. By retrieving anonymized GPS data from Google and Apple databases, referring to 4 billion of individuals, it was possible to deduce estimates for specific emission variations. Surface transport saw decrease of related emissions from 40 to 70%, Industry from 30 to 50%, Residential from 5 to 20% and Public/Commercial from 20 to 60%. Another study [4] obtained different results with different methods; input data included for the power sector European electricity trends and coal use data, traffic data for the transport sector, in a similar way to the first study, and smart meter data for the residential sector. Variations for the commercial sector were inferred. Their results show emission reductions for the Power sector from 2 to 14%, for Industry from 10 to 30%, for surface Transport from 30 to 50%, for Public and Commercial from 8 to 30% with a median on 20% and increases for Residential sector from -1 to +7% with a median on 3%.

Table 1.1. Emissions variations during 2020 initial lockdowns

Paper	Public and Commercial	Residential	Industry	Transport	Power
Le Quéré, C. et al. [4]	-20 (-8 to -30)	3 (-1 to 7)	-20 (-10 to -30)	-36 (-28 to -46)	-7,4 (-2 to -14)
M.Forster, P. et al. [11]	-50 (-20 to -60)	15 (5 to 20)	-40 (-30 to -50)	-50 (-40 to -70)	-

Even if the registered changes in emissions are entirely due to forced reductions in energy demand, the overall effect may provide quantitative indications of the potential impacts and limits that strong structural changes could deliver if persistent and implemented in the future. Working from Home above all has the potential of being structurally adopted by countries all over the world in the near future, as demonstrated by multiple studies. The extent of disruptions caused by the pandemic affects not only the technical and energy demand sides but even more prominently involves behavioral aspects, induces legislative frameworks to adapt at new scenarios and has the potential to accelerate changes in the job market and economy sectors that were already taking place. [35, 42]

World nations are now (March 2021) struggling to vaccinate most of their population in the shortest time allowable, to be ready for the great economic recovery that will be financed with unprecedented investments worth trillions of dollars. The biggest challenge for the World is to succeed in combining economic stimulus with sustainable investments. [43] The next ten years will be crucial to avoid exceeding the temperature thresholds limits of 1.5°C and 2°C set by the Paris Agreement of 2015. Emissions in late 2020 were seen beginning to rebound and so far “potentially damaging contributions” label the stimulus packages of 21 major economies, including United States, China and India. [44] Reality is that the longer-term shape of the recovery is yet to be defined and most remain in the hands of policymakers who must prioritize fundings with neutral or “friendly” contributions to carbon budgets.

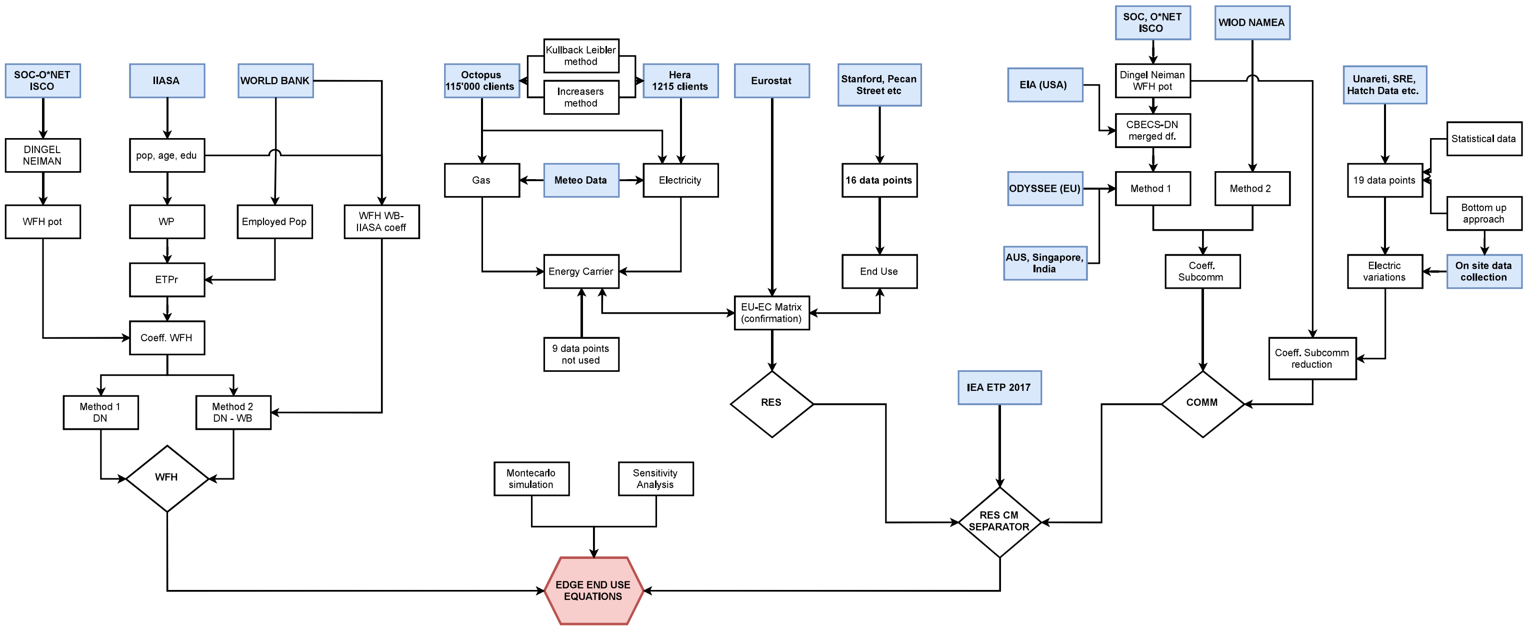
The contribution of this research in an optic of first approach to the phenomena is thereby to verify if Working from Home (WFH) can have a “friendly” or “damaging” contribution to carbon budgets, and analysis will be restricted to the Building Sector. If found to be overall energy saving, excluded others conveniency parameters, WFH could be included among those measures that policymakers should favor in the next years to comply with climate treaties. It must be highlighted that there is few or no literature published yet, that try to frame a world energy-Work From Home scenario as is done in this study. There is therefore space for many improvements, as will be mentioned further in the document, and as is allowed by the flexibility of the EDGE model upon which are based all the simulations.

1.3 Thesis Structure

The structure of the thesis report is the following:

- In Chapter 2 is performed a general description of Integrated Assessment Models (IAMs), with a focus on the Energy Demand GEneration Model (EDGE) which was used in this research.
- In Chapter 3 is presented the sequence of assumptions and changes to the EDGE model that allowed for the simulation of a Work From Home Scenario in the Building Sector.
- In Chapter 4 results from a Monte Carlo simulation are presented along with a sensitivity analysis performed on the new model inputs. In a final section are summarized the key findings.

In the next page is presented the general structure of this research, where blue-coloured rectangulars represent source of data.



SOC-O*NET ISCO
DINGEL NEIMAN
WFH pot
IIASA
pop, age, edu
WP
ETPr
Coeff. WFH
WORLD BANK
Employed Pop
WFH WB-IIASA coeff
Method 1 DN
Method 2 DN - WB
WFH
Kullback Leibler method
Increasers method
Octopus 115'000 clients
Hera 1215 clients
Gas
Meteo Data
Electricity
Energy Carrier
9 data points not used
Eurostat
EU-EC Matrix (confirmation)
RES
Stanford, Pecan Street etc
16 data points
End Use
Montecarlo simulation
Sensitivity Analysis
EDGE END USE EQUATIONS
IEA ETP 2017
RES CM SEPARATOR
SOC, O*NET ISCO
WIOD NAMEA
EIA (USA)
Dingel Neiman WFH pot
CBECS-DN merged df.
ODYSSEE (EU)
AUS, Singapore, India
Method 1
Method 2
Coeff. Subcomm
COMM
Unareti, SRE, Hatch Data etc.
Statistical data
19 data points
Bottom up approach
Electric variations
On site data collection
Coeff. Subcomm reduction

Chapter 2

Methods

"The purpose of IAMs is not to figure out what is going to happen in the year 2100, rather to figure what kind of steps we should do today, but that is impossible without long term projections." [45]

William Nordhause (2018 Nobel Prize in Economic Sciences, received for integrating climate change into long-run macroeconomic analysis)

This chapter has the following paragraphers. Section 2.1 briefly presents a summary of how Integrated Assessment Model perform world energy simulations. Section 2.2 introduces the set of Shared Socioeconomic Pathways upon which is based EDGE and this research. Section 2.3 introduces Building Modeling as deployed in EDGE, with a focus on sections of particular interest for this research.

2.1 IAM and global supply-demand energy models

IAMs were developed to provide long term analysis and strategies, in particular for climate change mitigation. They are designed to favor science-based planning, with the purpose of understanding how human development and societal choices may interact and affect the natural world. The suffix "Integrated" signals that they include contributions from different sciences, needed to grasp the complexity of Earth systems. Most of IAMs include sub models that frame assigned phenomena. Energy models are fundamentals blocks, as they directly relate to GHGs and given the relative weight of energy related emissions. Some models are even more specific, as they model only particular sub sectors. [46] It is the case for Building Energy models, that project with high levels of detail energy demand and other indicators.

In order to reduce emissions in the Building Sector, inverting actual increasing trends and reaching reductions of 7%yr (1.5°C scenario), it is needed a punctual modeling of principal drivers for buildings energy demand. All principals Building energy models try to provide the following insights:

- Estimations of baseline energy demands, through a review of existing building stocks, with different spatial resolutions. They can be country specific, regional, or having different aggregation criteria.

- Estimations of the impacts that different policies and technological improvements could deliver on the sector, with different spatial and time resolution. Projections are often considered reliable for mid of the century while those extending up to 2100 bring increasing levels of uncertainties.

- Identification of the effects of emission reduction policies on indoor comfort.

Results provided by this groups of models, and IAMs in general are not to be taken as exact projections of the futures, but rather serve to policymakers as indications of which future scenario actual trends could lead to, and which countermeasures should therefore be implemented. Building models projections should help politics and planner to understand better the dynamics and fundamentals needed to reduce emissions. Some adverse or beneficial processes results evident only when long term projected and when provided with assumptions coming from other sectorial models. It may be the case of energy demand projections taking into account population projections produced by socioeconomic models.

Modeling of energy demands require a careful identification of the main drivers and their selection as model inputs, with criteria that are often based upon their associated confidence levels. Two main approaches can be identified:

- **Top Down**: they start from estimates of energy consumptions for the building sector, and the review of a set of chosen variables allows to find structural correlations.

- **Bottom Up**: they require the implementation of chosen “artificial” drivers, energy demand for singular units is then calculated and results are aggregated at the desired level. Iterative calculations allow for the calibration of equation blocks.

EDGE Model is a Bottom Up approach, a brief review of those models is provided. Main implementations of Bottom Up models are the following:

- **Statistical Models**: they are based on historical datasets and regression analysis, with the purpose of linking Building final energy demand to End Uses and Energy Carriers, and of estimating future levels of demand in relation to variations of inputs. They are accompanied with relevant degree of uncertainty but can incorporate significant temporal dimensions and spatial extensions.

- **Engineering (thermal) Models**: widely used by scientific community, they account explicitly for energy consumptions of building structures. The set of input parameters is composed by a wider variety of thermal coefficients, accounting for specific efficiency performances or environment boundaries. They can offer more accurate calculations, however they are rarely scalable (national or regional level) and less flexible.

2.1.1 Managing uncertainties in inputs

Variables are often highly intercorrelated and characterized with both temporal and spatial dependence. Temporal resolution is often yearly based in global models, while regional resolution can be increased at willing. As consequence, global analysis must go through a careful review of parameters, to keep under control uncertainties. Increasing complexity does not always increase neither the quality of results nor their informational contribution. Moreover unjustified complexities can harmer reproducibility of the model and paradoxically augment the possibilities of injecting unwanted and undetected dynamics in it.

The choice of a restricted set of well documented hypothesis can therefore be as effective as the collection and interpretation of high resolution data. Building sector in particular is affected by intrinsic difficulties in modeling due to the following reasons:

- Regional dependency of construction materials, techniques, regulations, floor space and environmental feedbacks.
- Behavioral issues substantially affect building energy uses. In fact it has been estimated that factors of 3 to 10 times differences may exists in residential energy use for similar dwellings with same occupancy and comfort levels, and 10 times difference in office buildings. [36] Detailed data collection would cost and require considerable amount of time and therefore is signaled the lack of adequate datasets for bottom-up analysis. [36] Databases do not often provide comprehensive capture of real building energy uses, and exceptions are confined to few cases.

Behavioral and lifestyle issues are crucial drivers of building energy use and quantitative modelling of the impact of future lifestyle show that, particularly in developed countries where specific consumptions are high, margins for deep reductions are possible. A comprehensive acknowledgment of their impact on Building sector would affect also designing stages, as was demonstrated. The risks for example of defining universal standards of “high efficiency”, in reality culturally biased, could lead to local increases in energy consumption.

However studies that include reviews of behavioral factors are scarce. This research has also faced the needs for a better understanding of cultural drivers. Uncertainties in building models may derive also from a variety of sources, descripted in [47]. Scientific community has therefore developed a set of scenarios, that should contribute in limiting uncertainty in models. They also offer a common ground of discussion and facilitate better understandability of different studies. These scenarios are temporally and spatially defined and their evolution in time is modelled by coherent and validated frameworks of hypothesis.

The Shared Socioeconomic Pathways (SSPs) are therefore powerful “tools” that can be adopted at multiple regional resolution extents. [48] They are not assigned with specific occurrence probabilities and propose the widest plausible variety of scenarios that humanity may face during the century. EDGE make advantage of the SSPs scenarios and produce different outputs coherently.

2.2 Shared Socioeconomic Pathways

Literature and bibliography about SSPs is vast and well documented. They will be used to produce the IPCC Sixth Assessment Report on Climate Change, which is due in 2021. First efforts to create shared and common socioeconomic scenario begun in the 1990s, when researchers from different modelling groups had developed the "SRES" scenarios. [49] The necessity of updates was clear as the years after saw rapid and deep changes in societies and world economies. Moreover a new way of tackling Climate Change modeling began being adopted. A first group of researcher would develop four Representative Concentration Pathways, or RPCs, spanning a broad range of human induced radiative forcing (2.6,4.5,6.0,8.5 Watt per square meter). [50] A second group of researcher would instead work on modelling how socioeconomic factors may change during the century. Principal drivers being adopted were population, economic growth, education, urbanization rate and technological development rates. The two model branches would then provide the basis for a wide set of Climate Change mitigation scenarios. RCPs would provide pathways for emissions trends and their temperature increases, while SSPs would indicate the ways in which societies could reach those emissions trends. Each SSP would therefore allow for different levels of climate mitigation. In Figure 2.1 are shown the emissions over time under all SSP baselines (grey lines) and under differrent mitigation targets (coloured lines), with radiative forcing limits analogous to the RCPs.

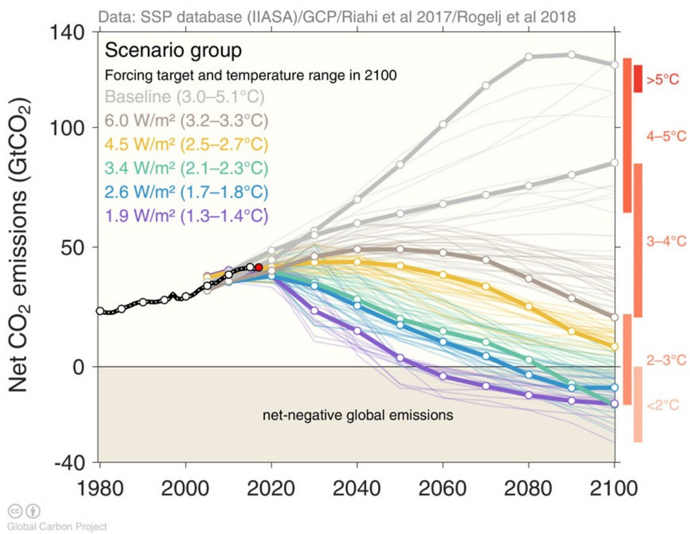


Figure 2.1. SSPs and RCPs

Shared Socioeconomic Pathways are five and they reflect different world narratives.

- **SSP1**: Sustainability- Taking the Green Road (Low challenges to mitigation and adaptation)
- **SSP2**: Middle of the Road (Medium challenges to mitigation and adaptation)
- **SSP3**: Regional Rivalry – (High challenges to mitigation and adaptation)

- **SSP4**: Inequality – (Low challenges to mitigation, high challenges to adaptation)
- **SSP5**: Fossil fuel Development (High challenges to mitigation, low challenges to adaptation)

In SSP1 the world shift toward a sustainable path, where inclusive development is emphasized. Educational and health investments are strong and accelerate the demographic transition. As a result, inequality is reduced across and within countries. Energy intensities tend to decrease.

In SSP2 the world does not diverge significantly from historical trends. Inequalities are reduced only slowly and environmental changes remain. Overall energy intensities declines.

In SSP3 rivalries and conflicts push countries to close and focus on domestic affairs. Investments in education and technological development declines and economic development is low. The lack of shared efforts to reduce emissions leads to strong local environmental degradations.

In SSP4 a gap widens between an acculturated society, internationally connected and highly productive, and a lower income one, poorly educated and associated to labor intensive markets, with low tech penetrations. Energy sector diversifies with investments in both fossil fuels and low carbon technologies.

In SSP5 the world manages to reach high levels in health and education but exploiting abundant fossil fuel resources. Energy intensive lifestyles are adopted, local environmental problems are successfully managed. Economies see their highest growth rates.

As will be analyzed further in the document, SSP3-SSP4-SSP5 are the most interesting scenarios for this research. In figure are shown exogenous projections for socio economic and climatic drivers at the global level used in EDGE. Population shows a net increase in the SSP3 scenario, its growth is in this scenario low in industrialized countries and high in developing countries. All other scenarios see reductions, strongest in the SSP1 (sustainable) one. Income per capita strongly rump up in the SSP5 scenario, thanks to a fossil fuel alimented growth, with the lowest levels in the SSP3 scenario. CDD (Cooling Degree Days) and HDD (Heating Degree Days) projections are computed from climate projections-SSP specific. Higher global temperatures were applied for the SSP5 and lower for the SSP1. The choice of the RCPs for each SSP implemented in EDGE is the following:

Table 2.1. RCPs and SSPs deployed in EDGE

SSP	1	2	3	4	5
RCP	4.5	6.0	6.0	4.5	8.5

As shown in Figure 2.2 the HDD and CDD trends do not reflect only climatic trends but also demographic ones, because data are aggregated based on the geographical distribution of the population. Expected demographic growth in Africa will bring down estimates for Hot Degree Days and raise those for Cold Degree Days. Their trends are also influenced by some behavioral characterization. For example, temperature thresholds change in the SSP1 scenario, which assumes the adoption of more sustainable consumption patterns among the population. Therefore, in the course of the century, the threshold of CDD will shift from 21°C to 25°C. Conversely, the reason why HDD does not fall in SSP1 after 2050 as is the case of other scenarios is mainly due to the reduced climate impacts (temperature growth) of SSP1.

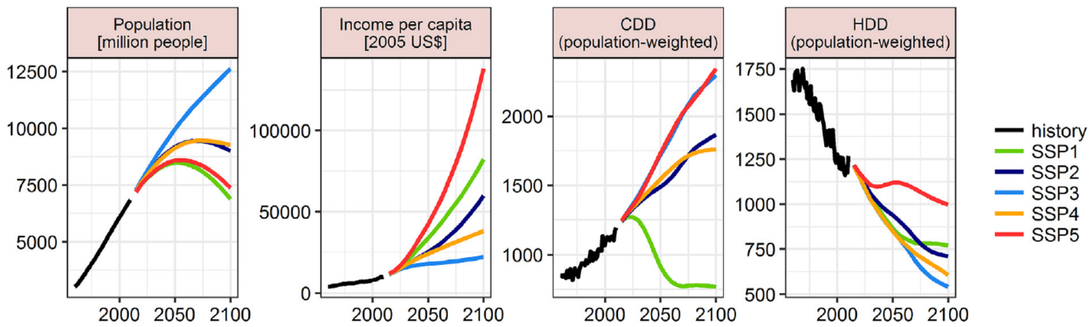


Figure 2.2. Exogenous drivers in EDGE

2.3 EDGE model

Considering previous analysis of current Building Energy Demands models, EDGE could be defined as a *bottom-up, statistically-based simulation model, with a multi-regional definition and built within a long-term time framework.* By the extent use of regression analysis it also makes advantage of macroeconomic indicators in order to gain general robustness. Its flexibility and customizability allowed for its integration in the REMIND (Regional Model of Investments and Development) IAM, [51] which is one of the six modeling platform being used for the upcoming IPCC sixth assessment report. [52] Both REMIND and sub-model EDGE were developed by the Potsdam Institute for Climate Research (PIK) in Germany. EDGE was then refined at Politecnico di Milano. In EDGE no price responsiveness was implemented.

Simulation mode: The model is executed sequentially, with no optimization. Regression analysis calibrations of socio economic drivers are first computed to then determine the evolutions of energy demands.

Time horizon: time step resolution is of 5 years, with a maximum time horizon that reach year 2100. The 5 years step enriches the model of the advantages of a long point of view while keeping at the same time reasonable computational times. This peculiarity was useful for the research, particularly when many computations were needed in Monte Carlo simulations. In this research time resolution was also occasionally artificially incremented to perform extra calibrations. The model assumes historical trends and relationship hold true in the short term, while longer in the future was projected a convergence towards lifestyles and consumption patterns peculiar of the SSPs narratives. (as was mentioned for the CDD,HDD).

Multi-regional: EDGE is divided in 11 macro regions, as shown in Figure 2.3. , with a country level implemented resolution for 28 European Union nations. It must be highlighted that most of data available in literature for the Building Sector derives from US and EU databases, and this fact justify the increase in resolution for EU. In fact, if needed, the same splitting could be applied within the United States, given the abundance of data. In the research external data with slightly different mapping were included.

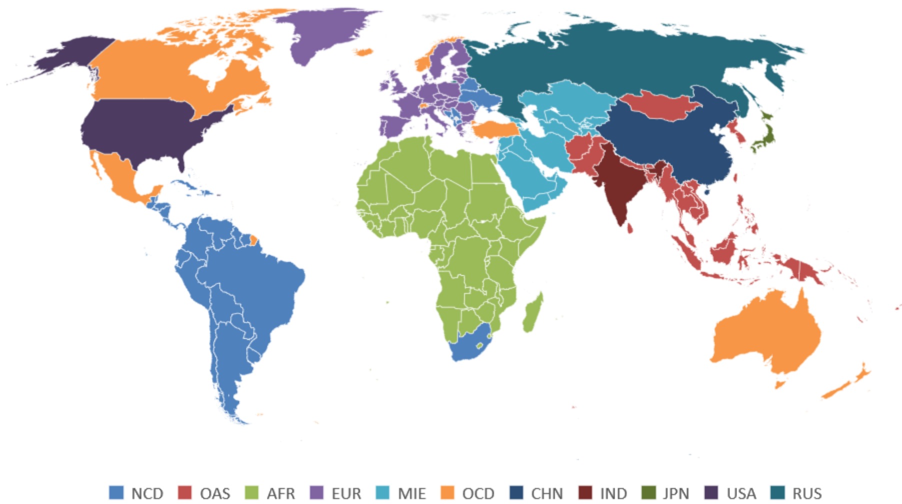


Figure 2.3. EDGE regions

Energy carriers and end-uses: EDGE is implemented with a 7 Energy Carriers resolution, that covers well world's different Building's energy portfolios. Electricity, traditional biomass, modern biomass (including pellets and improved fuelwood), coal, natural gas (also including biogas), liquids (including petrol, heating fuel oil and biofuels) and heat (district heating). In OECD countries (2018) around 75% of FED is covered by Electricity (37%) and Natural Gas (38%), while in developing countries shares of others fuels are higher.

Consumer perspective: EDGE does not model the Supply Side (generation) and therefore between-sector interactions or feedbacks are not contributing to the results. The model projects which energy carriers will be adopted or discouraged in time accordingly to the SSPs narratives.

2.3.1 Main concepts

EDGE documentation is available and provides clear explanations and justifications for the choices of parameters and the results of all regression analysis. However a brief review of the fundamental equations is presented. In this research most changes are on adjustments of the equation blocks, their characterization is therefore needed.

One of the most important peculiarities of EDGE model is the introduction of the concept of "Useful Energy", which allows for the comparison of energy use across regions at different stages of development. In the case of space heating, the

Useful Energy is the heat required to heat the room, which is in turn coming from a technology, eg. a boiler, alimented with an energy carrier, eg. natural gass or biomass. Useful Energy in this way allows for the decoupling of energy needs and the way in which these needs are satisfied. Useful Energy demands trends are computed for five different End Uses, Cooking, Water Heating, Space Coolig, Space Heating, Appliances and Lighting. The conversion in Final Energy Demand is made by relying on assumptions on energy efficiencies (Final to Useful Energy Efficiencies).

In Figure 2.4 is presented the way in which computations are performed in EDGE. Fundamentals drivers as Income, Population, Population Density, CDD and HDD are used to project Floor Space Demand, which is in turn an important parameter of the model, as it is used to perform many calibrations and to project FED. Then Useful Energy Demand is projected, without yet considerations on the supply side. Lastly Energy Carriers Shares are projected and Final Energy Demand is calculated. [53]

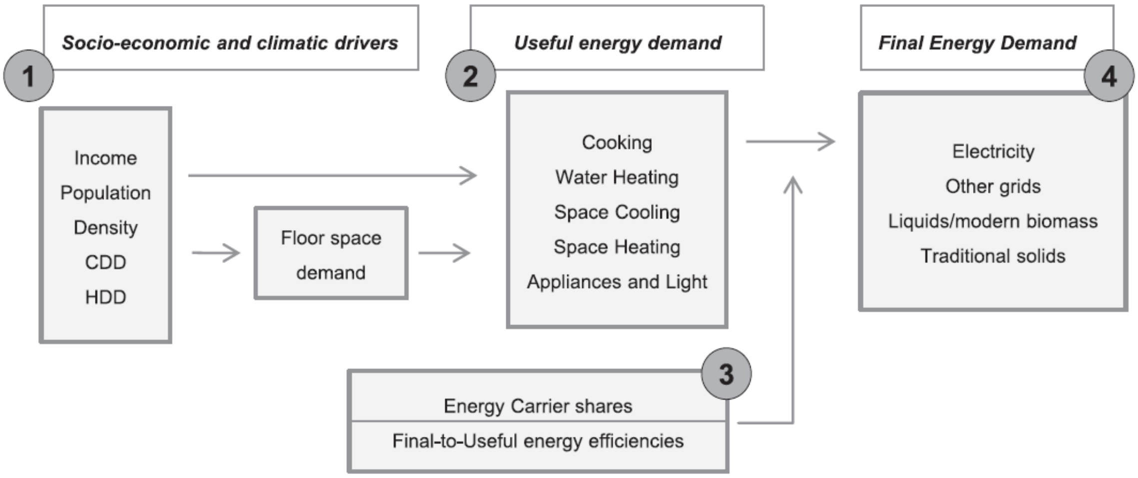


Figure 2.4. EDGE model logic flow chart

2.3.2 Main equations

Calibration parameters shown in the following set of equations are determined by imposing a match with present data and historical trends (that start from 1960-1990 and ends in 2015) and a convergence over long period (after 2100) to a certain value dependent on the SSP scenario. An example is presented in Figure 2.5. for the calibration of Space Heating.

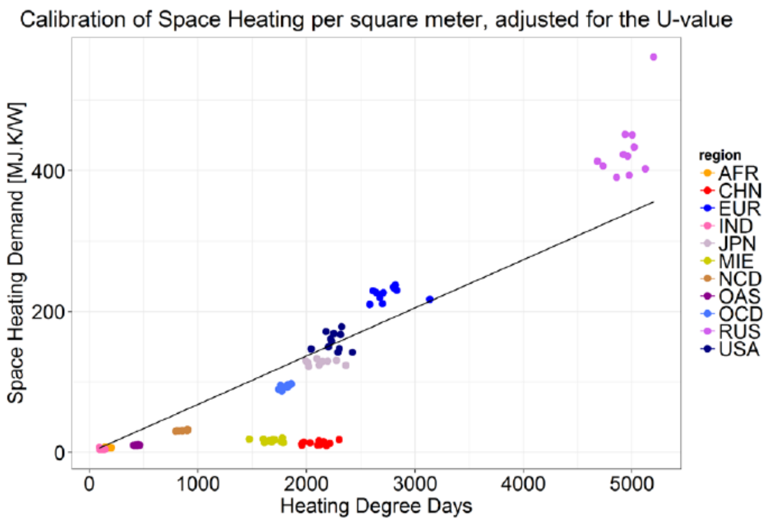


Figure 2.5. EDGE regression analysis for Space Heating

Floor Space per capita "F" is one of the most important equation in the model and will be further discusses as it includes both residential and commercial floor space. In fact in EDGE the two sectors are merged into the Building Sector at early stages. Historical data show that the positive relationship between wealth and floor space per capita holds even at high level of income, and this behavior is shown in the regressions. Floor Space is hence assumed to have a dependency on income per capita I, on population density D, as shown in equation, where t is the timestep, beta and gamma the elasticities of income and population density. These two parameters are obtained through a regression made on historical data. A stepwise regression is used, and future floor space demand is based on the value of the previous timestep. This equation calculates the residential floor space, while the commercial one is calibrated with a Gompertz function, by retrieving past data. For level of income per capita above 20000 US dollar (2005) the commercial to residential area ratio levels off close to 35%. Hence in developed countries growth in commercial space is projected to close growth levels of residential space, being saturation levels far in the future.

$$F_t = F_{t-1} + (\frac{I_t}{I_t - 1})^{\beta_t}(\frac{D_t}{D_{t-1}})^{\gamma} \tag{2.1}$$

Space Heating demand is assumed to be influenced by income levels only indirectly through the increasing demand for residential and commercial space. It is computed basing on HDD, Floor Space per capita (total), U values and on a positive parameter deltaheat. The final convergence of this parameter is obtained through regression on historical data.

$$\frac{SH}{F \cdot POP \cdot U} = \delta_{heat} \cdot HDD \tag{2.2}$$

Space Cooling demand modeling is more detailed, as it reacts in complex manners to electrification rates, purchasing power and to climate feedbacks (increase in air temperature). As example of purchasing power influence, can be the penetration of air conditioners in relation to income levels. Use of conditioners increase with electrification rates, which ultimately increases with income. But, as in 2014, 1.2 billions people lived in hot regions without access to electricity. Moreover at low income levels customers prioritize buying of other appliances instead, like refrigerators, TV or fans. Both effects imply low conditioners penetration rates at low income levels. Space cooling demand and CDD do not increase indefinitely with income. Once reached a “satisfaction level” saturation occurs. These considerations are implemented in the model through the definition of a “Climate Maximum” and of a logit cumulative curve.

Climate Maximum (CDD) assumes that in regions with only few hot days a year, the penetration of conditioners will remain low, independently from the growth of income level. Economic availability does not imply per-se customers purchasing products not needed. By contrary, installed air conditioners consumptions increase linearly with CDD.The logit cumulative curve, function of income, is a way to model a variable marginal willingness to install conditioners. Marginal willingness is low for low and high levels of income and high for medium levels of income.

$$\delta_{cool} = \frac{\phi_1}{1 + exp(\dfrac{\phi_2 - I}{\phi_3})} \tag{2.3}$$

$$\frac{SC}{F \cdot POP \cdot U} = CDD \cdot \delta_{cool} \cdot ClimateMax(CDD) \tag{2.4}$$

$$ClimateMaximum(CDD) = 1 - 0,949 \cdot e^{-0,00187 \cdot CDD} \tag{2.5}$$

Appliances and Lighting demand covers a range of devices that span from refrigerators to computer and dishwasher. Lighting accounts for all energy consumption producing light, however in EDGE they are grouped together and that is justified by the small relative weight of Lighting in relation to Appliances (mostly 20% of Appliances for OECD countries in residential sector and 30% in Commercial sector). Energy demand for Appliances and Lighting is projected to grow with income levels without saturation in EDGE. Share of electronic services in the commercial sector is projected to increase, as they will serve as tools to increase productivity. Commercial sector itself is projected to increase along with income levels, and the two effects combined justify the absence of a saturation level. The relationship between income and energy demand is modeled through an income elasticity on demand which decreases with increasing income levels. Beta is a parameter influencing the speed of convergence and alpha is a scenario specific parameter.

$$\sigma_{income} = \phi_1 + \frac{\beta}{\sqrt{I}} \tag{2.6}$$

$$Appliances\ and\ Lighting = \alpha \cdot exp(\phi_2 + \phi_1 \cdot log(I) + \frac{\gamma}{\sqrt{I}} \tag{2.7}$$

Cooking is implemented through a simple relation and it is modeled as being independent from income. Regional differences in cooking useful energy demand are thus product of cultural and geographical patterns. All cooking demands converge toward a value in the long term with differentiated speeds accordingly to scenario assumptions. It is important for this research to evidence that in Africa two thirds of final energy demand is due to cooking.

$$Cooking = \alpha \tag{2.8}$$

Water Heating useful energy demand is projected to increase with income, however in a similar fashion to space cooling equation a saturation level is included through the definition of a logit curve.

$$Water\ Heating = \frac{\phi_1}{1 + exp(\frac{\phi_2 - I}{\phi_3})} \tag{2.9}$$

FE UE Efficiencies conversions are modeled via functions that relate energy efficiency to income and allow for a maximum of one, accordingly to energy conservation laws. The exception is for Heat Pumps and Air Conditioning systems. The parametrization of efficiency functions is specific for each combination of energy carrier-end use. Concerning energy carriers shares assumptions are made regarding energy ladder and shifting of fuels in high income economies. It is first predicted that the use of traditional fuels will decrease toward 1% as the income approaches 20000 dollars/cap. Then for modern fuels, the assumption is of an energy carrier specific share convergence level.

$$efficiency = \phi_1 + (\phi_2 - \phi_1)exp(-exp(\phi_3)income) \tag{2.10}$$

Chapter 3

EDGE advancements

"The amount of uncertainty and lack of consensus on the energy and environmental benefits of teleworking has arguably contributed to the lack of coordinated promotion of teleworking by business or government, even in countries where multiple studies have been conducted."

Hook A et.al (Environmental Research Letter, 2020) [54]

This chapter presents the contributions of this research in defining a coherent Work From Home scenario for the Building Sector. In its nature of a sector-specific study, it can be taken as one the very first modeling attempts, of recent years. A coherent review work made by A.Hook et al. (Environmental Research Letter 2020) [54] found 39 papers published in the last twenty years, that tried to grasp the effects of teleworking on energy consumption and emissions. However, most of them were published before 2010 and contained therefore old data, these papers moreover could not forecast the abrupt exogenous shocks induced by the COV19 Pandemic. Lastly the vast majority of them focused on commuting and transport side effects of teleworking while only a minority, 8 studies, included consideration on Building consumptions. Of these 8 papers all of them were country or region specific, and only 5 considered both Home and Residential Consumption with a modeling approach. All these 5 papers were published between 2003 and 2008. In this contest, the contribution of this work is mainly to extend in a rigorous way modeling to a global level, coherently with EDGE regional mapping, and to increase the informational resolution of analysis with considerations on End Uses variations and Energy Carriers.

The structure of the chapter is the following: a first section 3.1 presents Working From Home, and its modeling in EDGE. Section 3.2 the attempts of separating commercial and residential sectors. Section 3.3 the subcommercial separation. Section 3.4 Commercial consumption variations observed and modeled in EDGE. Section 3.5 is dedicated to Residential consumption variations. In Section 3.6 is presented the final set of new equations implemented in EDGE.

3.1 Working From Home

Working From Home is by definition a work arrangement in which employees do not commute, and so do not move from residential buildings to the place of work by means of private or public transports. [55] Another term used for defining this emerging trend is “telecommuting”, a word which pinpoints to the role of telecommunication technologies in favoring WFH. Teleworking or “telecommuting” has been for almost three decades forecasted to substitute ordinal work, and its presumed beneficial impacts on environment, business and worker lifestyles were brought as justifications for a quasi-obvious future adoption in world countries. In the 1990s slogan as “Work is something you do, not something you travel to” were coined, in a general atmosphere of enthusiasm and idealization. Yet, after 30 years, a considerable but surely lower than expectations percentage of workers were in WFH regimes, around 5,2% in European Union in 2018, accordingly to Eurostat. [56]

The concepts of Telecommuting and Telework are similar but yet some differences are important for the purpose of this research. In fact all types of technology assisted work conducted outside a centrally located work space are classified as Telework. The substituting work place can be the worker house or others remote workplace as shared coworking offices or coffee. However this research limits the complexity of the phenomena and considers Work From Home (as the word says) having a univocal possibility of substitution between an office workplace and home based workplace. Coworking related issues, along with similar phenomena as “distributed work”, “hoteling” and “digital nomadism” (referring to the possibility of working almost everywhere in the world, travelling from location to location) are therefore not analyzed. Their relative importance for the modeling of WFH could however increase in the future, as they relate to behavioral and psychological wellbeing of workers. [57]. The sense of isolation and conversely the needs for social interactions hampered by WFH were in fact among the factors that limited its adoption. [58].

Another simplification made in this model refers to the averaged working days in WFH regime per home worker. Telecommuting does not require per se a fully work at home regime, in fact a survey conducted by Linkedin in 2019 had found that of 2000 working professionals 82% preferred working at home at least one day a week and 57% three days a week [59]. The majority of WFH simulations however, along with this research, congruently with data taken as sources, consider WFH as a job entirely performed at home.

3.1.1 WFH: Adoption Justifications

WFH is implemented in this research as a structural change. It is projected as a long-lasting trend over the century and its adoption ratio are monotonically increasing ones, as will be explained further in the chapter. Here is provided briefly a list of considerations that justify the theory of the phenomena and try to answer the question of “why is WFH being adopted”. The identification of drivers instead in a formal approach is presented instead in other sections.

A way to explain potential benefits of Working From Home and therefore to justify its “reason” of adoption in countries around the world is to refer to the “Job Characteristic Theory” (JCT), [60, 61] that explain how traits and tasks of jobs may influence work attitudes and behaviors. In particular, the JCT identifies five key characteristic of a job that, if present, have the potential to deliver higher job performances, more internal work motivation, and improve general satisfaction levels. Of these five characteristic, which are “Skill Variety”, “Task Identity”, “Task significance”, “Autonomy” and “Feedback”, telework specifically affects Autonomy and Feedback compared to traditional face to face (F2F) work. Not surprisingly, according to JCT theory, changes in Autonomy influence work behavior more than changes in other four characteristic.

Autonomy: One of the most evident and publicized benefits of WFH is the relaxation of working routines and the possibility for a worker to manage in better ways free time. If a job provides scheduling flexibility and more independence, the worker should feel more responsibility on own outcomes. At the same time, more independence would imply more accountability, which is a desired feature of work processes. [60] The possibility of choosing the workplace, principally worker’s house, allows also for the reduction of work-family conflicts.

Feedback is instead potentially negative affected by WFH, as digital communication may increase difficulties in interpreting and gaining information. Ambiguity in processes could increase, as in jobs assignments. However with the increase in technological progress the chances for better digital communication are higher, and difficulties in communication may be resolved.

Other principal advantages that WFH could bring are relative to the company side. Reduced personal in offices have the potential to imply lower operation and maintenance costs, as electricity and gas bills. High levels of WFH for a company can imply lower needs for office space, thus reducing also renting costs. Hiring professionals from around the world becomes an option, that can in turn improve productivity, which is also increased by workers potentially improved performances. [62] Other benefits relates to lower traffic congestion rates and reduced pressure on transportation infrastructure due to less commuting to work places.

3.1.2 Historical Trends

Interest in Working From Home has been growing constantly in the last ten years, with shares of adoption increasing at constant rate, especially in developed countries. Some historical trends are provided.

EUROPEAN UNION: As in 2017, European Union average share of WFH, entirely performed from home, was of 5% (of employed population), while the share of usual work from home was slightly higher, 9.6% [56]. A great variety in shares was registered among member states, with countries as the Netherlands having levels of 14% and Greece of around 2%. Data from 2019 Eurostat datasets show that some countries, as Austria and Norway, saw their WFH shares remain flat in the last ten years, keeping on levels respectively of 10 and 5%. Others like Portugal and Finland saw instead WFH increasing quite constantly from level respectively of 1 and 9% to 6.5 an 14.1%. The ninefold registered increase for Portugal and the 40% registered for the Netherlands, that saw a 10 year increase from levels of 10% in 2008 to 14% in 2018, signal the presence of different marginal rates of WFH increase, as will be discussed further in the chapter. In UK as is shown in picture Figure 3.1 , WFH rates saw a sharp increment from 2010. Just one month before COV19 in February 2020, around 5% of the employed population was exclusively working at home according to a report released by WISERD (2020) [63].

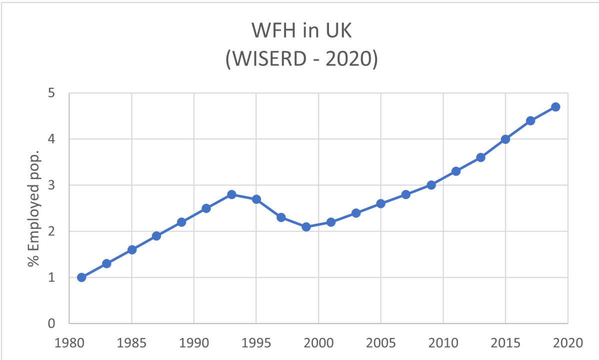


Figure 3.1. WFH in UK prior 2020

UNITED STATES: According to a report released by the US Census in 2018, 5.4% of US employed population was working entirely from home, while the share of American that spent at least some time working remotely was of 43% in 2017. The share of WFH had been growing constantly in the last twenty years, from levels of 3% in the 2000s. In the years 2012-2016 it was registered a change also in average time spent working remotely, if in 2012 the share of workers spending >80% of their work time remotely was of 24%, four years later had increased up to 31%. The chart in Figure 3.2 retrieved from a US Census 2010 report, [64] show that similarly to European Union, great difference exist within US States (the chart shows US Metropolitan Areas, colored), with states like California showing their metropolitan areas average levels of WFH from 5% over, while others like New York State and Maryland being below 5%.

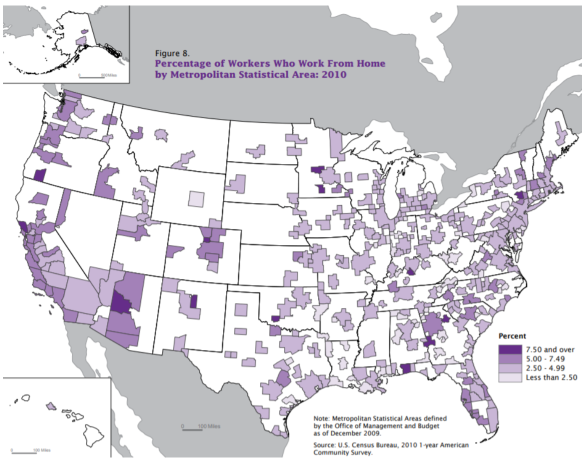


Figure 3.2. WFH in US prior 2020, U.S Census

Australia is cited as a data collection from this country will be performed as explained further in the document. Work From Home historic data are scarce, however Australian government reported for 2010 a share of 5% of WFH, while the share of workers that spent at least 10 hours each week working from home was of 20% in 2016, and had remained constant throughout the previous ten years. Data for developing countries were not found prior to COV19 pandemic, mostly because registered levels were statistically unsignificant and for the absence of national accurate census bureau.

3.1.3 WFH New Levels amid COV19

The spreading of the COVID 19 pandemic destroyed lives and ravaged economies all over the world. Epidemiologist and World Health Organization experts highlighted as first containment measures the importance of social distancing measures, that eventually led to the installments of Shelter in Place orders (SIP) all over the world. At its peak in April 2020 around 50% of world population was confined at home. [65] As consequence, in order to secure continuity of business operations, governments across the world encouraged those who could, to work from home. In mid-April 2020, 59 countries had already implemented telework. [3]

At European Union level, data are provided by the "Eurofound's Living,Working and COVID-19 survey", [1] which received 62755 completed responses in the EU27 member states during the first wave of lockdowns and 24123 responses in a second round in June-July 2020. Across Europe as a whole around 48% of employed population was reported at WFH, 34% of whom were working exclusively from home and 14% partially. Regional differences resembled the pattern pre crisis. In Finland WFH levels reached 60%, in Luxemburg, Netherlands, Belgium and Denmark were of 50%. Figure 3.3 In UK WFH skyrocketed from ten years levels of around 5% to 45% in less than a month.

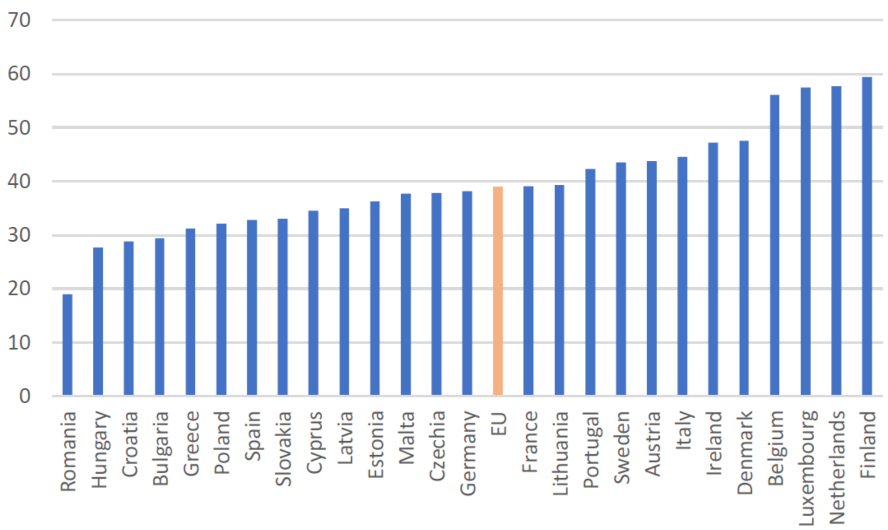


Figure 3.3. WFH in EU amid COV19, survey of April 2020

It must be stressed that the reliability of this data is only provided by the relatively high number of surveys responses, in fact official publication from EU bodies have yet to be produced. Some contradictory data appears when the Eurofound survey dataset is consulted upon the question "Location of Work-Home" for the period June/July. Italy is shown having positive responses of 53%, while Finland, which was stated having the highest WFH levels, is assigned a positive response ratio of 47%.

United States data were first released by the National Bureau of Economic Research (NBER) in June 2020. [66] The surveys were collected in two rounds, a first in April and a second in May 2020. The respondents were in both cases 25000. The fraction of workers who switched to working from home was of 35%. An additional 15% of workers indicated that was already in a WFH regime prior to the COVID19 pandemic. Data would lead to a percentage of 50% of US employed workforce being at WFH. However this percentage is significantly higher than others studies for which the average was instead of 37% at WFH (Dingel Neiman, 2020) [7]. Moreover a prior COVID19 percentage of 15% contradicts US Census prior COVID19 indicated levels of 5.4%. Reliability of US Census statistics is higher, a possibility is of misinterpretation by survey's respondents of questions regarding the extent of WFH in hours or days a week. WFH stands in fact for a permanent full week working regime.

Some of the surveys mentioned in this section also contained useful information about gender, employment status, age and economic availability of the respondents. These data were usefully exploited by other studies and allowed for a calibration of the probability of Working from Home, relatively to these and others macro indicators. Moreover, the tenfold increases in WFH levels aforementioned show that market structures and infrastructures needed for much higher WFH levels are already available, at least in Developed Countries. COVID19 pandemic was therefore the exogenous shock that allowed for the collapsing of social and economic inertias and the reaching (and in some cases exceeding) of full WFH potential.

Data for Developing Countries are not reported in this section, considerations are shown in the next one.

3.1.4 WFH Implementation

Work From Home was implemented in EDGE following two approaches. A first one considered as theoretical justification a working paper published in April 2020 by the National Bureau of Economic Research, NBER (Cambridge, Massachusetts, United States), [7] a second one tried to upgrade the first implementation by relying on a working paper published by the World Bank Group in May 2020. [8] The latter included itself an extensive review of the paper published by the NBER. The most cited works regarding WFH characterization following COVID19 pandemic of 2020 were respectively the work done by Jonathan I. Dingel and Brent Neiman of NBER, "How many jobs can be done at home?" and the working paper of Fernando Saltiel "Who can work from Home in Developing Countries" of Duke University, published in April 2020 [67]. Dingel and Neiman working paper was then used for rough estimates of working from home potential impacts on energy uses by the International Energy Agency, (IEA) [9] it was also cited as most reliable data source by the International Labor Organization (ILO). [3] References to this work were also present in the

European Eurofound working paper published in 2020 [1] and mainly in every paper consulted reporting analysis, considerations or data about allegedly registered WFH national levels during COVID19 pandemic and about their relative future potentials.

For these reasons it was decided to model Work From Home in EDGE Buildings giving more “weight” to Dingel and Neiman (DN) model. However, being DN work one of the first of its kind, it contains simplifications and assumptions about work type descriptions that are mostly US based. In this sense upgrades to this model were already available as in mid-2020 and were mostly contributes from the others working papers mentioned. In a second round outputs produced by the DN model were therefore slightly corrected to account for these improvements. However purpose of these corrections in EDGE model was not the production of more accurate outputs, given related uncertainties, but rather providing the general structure of a more complex modeling framework that could possibly be exploited by future works. Scenarios are therefore presented separately, first with only DN implemented, then DN plus possible improvements in WFH phenomenology.

First Method

Dingel and Neiman tried to answer a fundamental question, “How many jobs can be performed at home?”. To do so they used surveys describing the tasks of more than 1000 US occupations and they classified each of them as able or unable to be done entirely from home. Data for US shown that around 37% of jobs in the US could be WFH occupations, with variations across metropolitan areas and industries. Then they extended their method to other 85 countries and they found a strong correlation between WFH levels and GDP per capita. Developing countries with per capita GDP levels below a third of US ones resulted having around half WFH potential levels. The correlation found by Dingel and Neiman, made available on GitHub to scientific community were then inserted in EDGE, which includes GDP and Population Projections SSP specifics, and projected for all EDGE regions. In order to understand the robustness of this method a brief review on why GDP and WFH levels correlates must first be presented.

Classification of Occupations The underlying logics of all recent works that tried to grasp correlations useful to predict WFH levels among population groups and countries was the following:

1. Extract information about working population, collecting data mostly about gender, age and education levels of each surveyed worker.
2. Develop a method to define if a specific occupation can be done from home.
3. Aggregate data and find the probability of an occupation to be WFH in relation to the drivers (plus other) identified in 1.
4. Identify macro patterns from aggregating shares relative to occupational groups.

A fundamental source of data was the O*NET database, developed and maintained by the US Department of Labor. It contains descriptors and standardized surveys for 1000 occupations that allow to understand if a job can be performed at home from listing the tasks usually required to be performed. Generally, the higher the necessity of physical contacts or face to face interactions (F2F) with clients the lower the probability of the job to be WFH (teleworkable). Dingel and Neiman decided to interpret the O*NET database by establishing a binary relationship between certain survey's question and the possibility of a job to be WFH.

Out of 57 questions present in the O*NET "Work Context Questionnaire" (WCQ) survey, seven of them were assigned a binary coding. Out of 41 questions present in the O*NET "Generalized Work Activities Questionnaire" (GWA), eight of them had binary coding. For example, if any of the three-following WCQ questions had positive answers, relative respondent occupation was assigned a probability equal zero to be performed at home.

- Do you use email less than once per month?
- Do you spend the majority of time wearing common or specialized protective or safety equipment?
- Do you work outdoors every day?

Also, as example, if any of the three following GWA questions had positive answer, the relative occupation was labeled as not teleworkable.

- Performing General Physical Activities is very important.
- Inspecting Equipment, Structures or Materials is very important.
- Operating Behicles, Mechanized Devices or Equipment is very important.

Dingel and Neiman then tried to asses the robustness of this method by following a semi-"Delphi" procedure, assigning arbitrarily probabilities (0-0.5-1) of WFH for each Standard Occupational Classification (SOC). [68] Results agreed for an 85% of cases with those provided by the O*NET method. By binding SOC database with the O*NET results, emerged that managers, educators, IT and finance workers, and lawyers were the occupations most likely to be performed at home. At contrary farmers and occupations in the construction and production sectors were the least. Overall, 37% of US occupations, basing on this method, was reported having high WFH potentials. Moreover, a strong relationship was found between income and WFH. The higher the wages, the higher the WFH probability. It was also found a strong positive relationship between education levels (college degree).

Critics to this method as chosen by Dingel and Neiman regard particularly the arbitrary choice of the number of surveys questions having a binary output. In fact, the higher this number, the higher the possibility of having at least one positive (zero WFH probability) answer. [8]

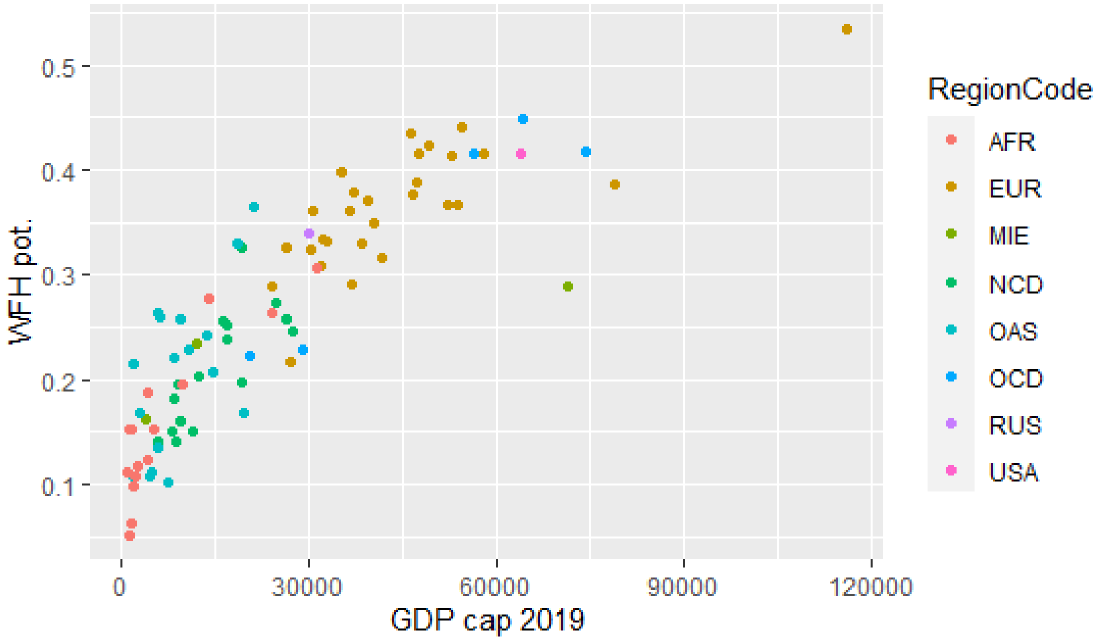
The way in which these results were extended to other world regions is straightforward. Statistics found for US were aggregated (also) per US Occupation (SOC), these data were then bonded with the International Standard Classification of Occupations (ISCO). As Dingel and Neiman reports in their paper, this method involves the extensions of US based assumptions on a world level, possibly causing distortions in results.

In fact critics highlight that despite having the same Occupational description (SOC and ISCO), the nature of tasks, upon which is based the WFH probability method, could vary among countries. This in particular is the reason why in EDGE was implemented also the second method.

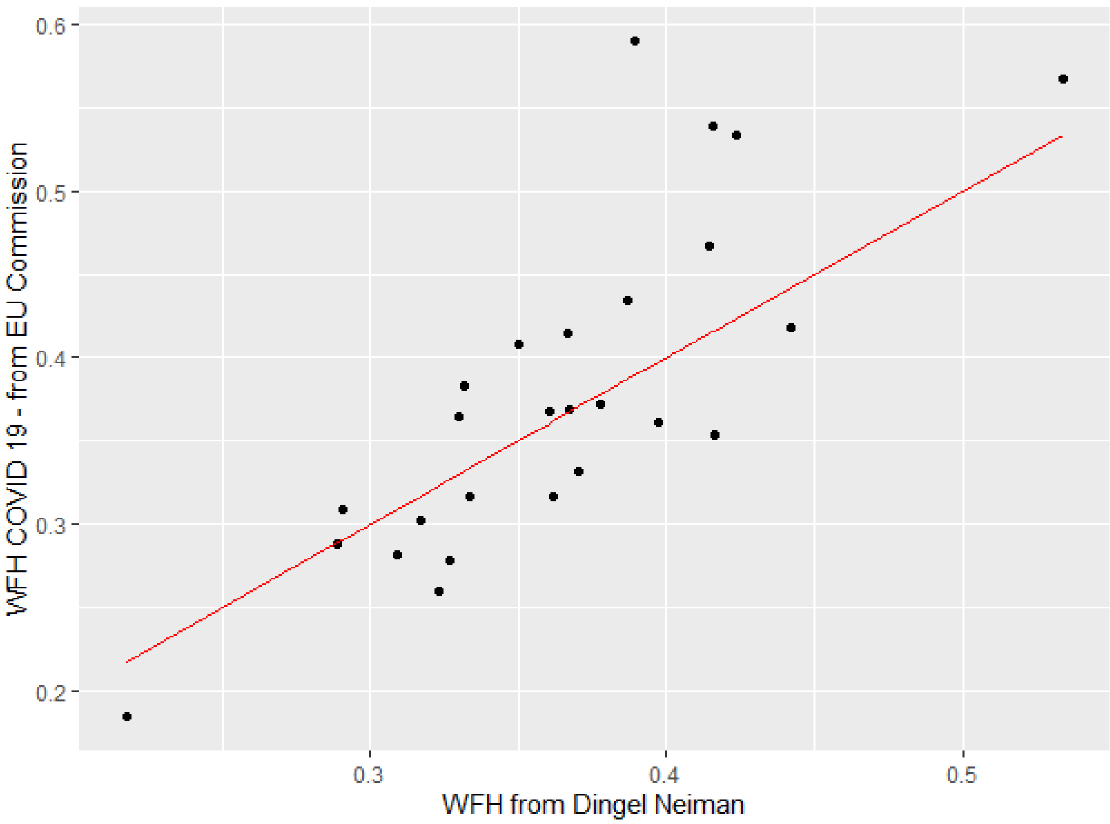
Results obtained by correlating SOC inferences to the ISCO one were then aggregated by country and then at world level. In the next page are shown the datapoints and a comparison performed by Dingel Neiman between potential (EU) WFH levels and those found during COVID19 pandemic, that shows a clear correlation pattern, with slightly higher percentage of registered WFH COVID19 levels.

First Method, EDGE In Figure 3.5 is shown the correlation implemented in EDGE in this research by extracting datapoints from GitHub and interpolating them in “R” program. Each dot represents an interpolating point (a country in the Dingel Nieman dataset). In order to project WFH levels in the future the model needed a function that could relate GDP per capita levels, region and time specific, to WFH levels. The interpolation function was found applying a General Additive Model (GAM) within the “mgcv” package in “R”. GAM solves the smoothing parameter estimation by using a Generalized cross Validation criterion (GCV). R square was equal to 0,84 and RMSE (Root Mean Square Error) 0,048. The advantage of using the “mgcv” package is that the choice of the regression splines is automatic and made by assigning penalization criteria in a contest of general optimization. The obtained interpolation function, having ten coefficients was then called by the program each time it was needed the calculation of a WFH potential. The general shape of the interpolating function shows a particular behavior. First it grows rapidly with the increase of GDP per capita, then the derivative decrease until a plateau is reached for values of approximately 60000 dollars/cap. Then it starts to grow again with derivative circa constant. Four important considerations must be highlighted:

First Consideration: The behavior of the curve is still yet to be explored. A necessary premise is that purpose of this research was not strictly a WFH characterization but rather a study of the energy consequences of a wide WFH adoption around the world, therefore the following hypothesis are to be taken as speculative and not necessarily accurate. With this assumption some hypothesis can yet be made about the non-linearity of the curve. The theory of Economic Convergence (“catch-up effect”) assesses that poorer economies’ per capita income tend to grow at faster rates than richer economies, and as a result all economies tend to converge to similar value over time, provided regional exceptions. [69] As was found in Dingel Neiman, WFH is linearly related to the median hourly wage, where median means the average of



(a) WFH gdp regression



(b) WFH amid COVID19, EUR only

Figure 3.4. Dingel Neiman Results

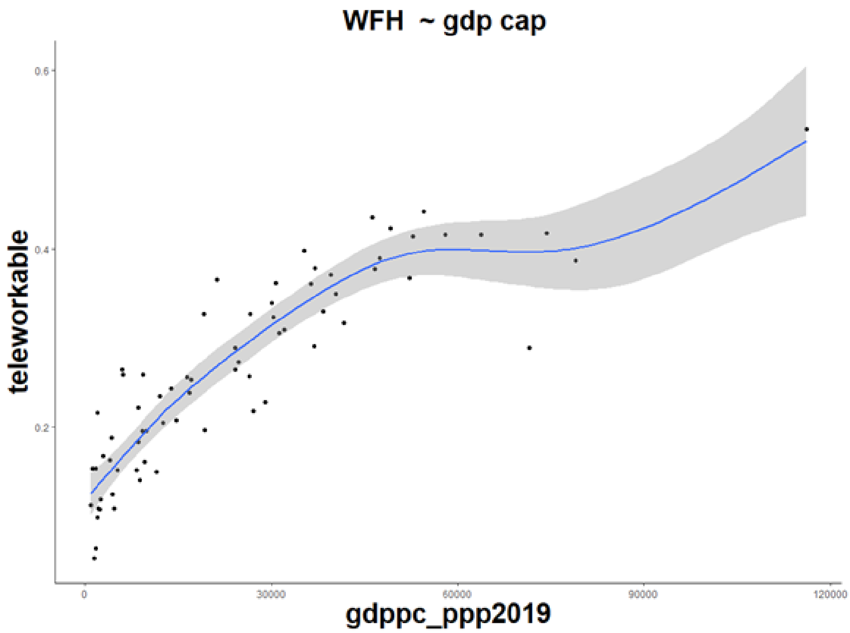


Figure 3.5. WFH correlation

the same occupation wages. Figure 3.6. Assuming, as the economy grows, a shift from low wage low productivity jobs towards higher wage higher productivity jobs (eg less workers in the agriculture sector), also the average value of WFH should increase. Average here means all occupations-average. But the speed of economic growth in the convergence theory is higher for lower value of GDP per capita, therefore also the growth of WFH should be higher for lower value of GDP per capita, as the interpolating curve show.

Figure 3.6. WFH and hourly wage correlation, Dingel Neiman

Second consideration: the interpolating curve is kept constant over the century. The underlying modeling assumption is the following. If a country X reaches a GDP per capita level of eg. 30000 dollars in year 2050, it will have an assigned WFH potential level of 31%. If a country Y reaches the same GDP per capita level but in the year 2080, it will reach again a WFH pot level of 31%. Another example the case in which GDP per capita does not grow, also WFH levels remain the same. It may be a too strong hypothesis, and in fact some corrections were made in Method 2 to account for other drivers. However, in the last twenty years, US and EU data have shown, as was reported in the "Historical Trend" section, a relatively small increase in WFH levels, in absolute values. Reported average values of WFH were both for EU and US of about 5% pre COVID19. This despite a constant GDP increase, a part from the recession and stagnation occurred in years 2008-2011. It could therefore be not unrealistic a modeling choice of stagnating WFH levels with stagnating GDP levels.

Third consideration: the behavior of the curve on its upper end is derived from only one observational point, which is Luxemburg, reported having a WFH potential of around 0,6 in 2019. The speculative nature of this behavior is clear yet it was decided to keep this datapoint in the model to simulate a sort of "best/worst case scenario" (it depends on final results in term of energy savings). The interpretation could be the following, after a "saturation" zone that stretches from 50000 to around 80000 dollars per capita, unknown dynamics in the fundamental of economies occur that favor WFH potential. They could be related to technological adoption rates suddenly increasing, purpose of this model was not the exact identification of such drivers. Moreover, in the absence of valid alternatives offering explanations on the relationship WFH GDP, it was decided to keep this behavior and see how the model would react to it.

Fourth consideration: WFH potential levels indicate the maximum rate of adoption allowed by Dingel Neiman interpolation. It could also be possible a scenario where in reality adopted shares are higher than those interpolated, this was considered in a Monte Carlo simulation performed on the results.

- In a first scenario all regions start in 2020 with WFH levels equal zero to reach their allowed potential in 2050. This scenario is equivalent to a one where WFH "boosted" COVID19 shares return to the pre pandemic levels. The choice of the "learning period" would be crucial in a model trying to simulate the exacts dynamics of working from home around the world, however EDGE is an energy model and thus of more relevance for the research were more the energy consequences, in magnitude.

- In a second scenario all countries start in 2020 with their real WFH levels equals to the potential one. Adoption trends than follow exactly those generated by the interpolating function. This scenario is a one where COVID19 induced WFH levels remain structural over time. It must be stressed that COVID19 per se in this second scenario only allowed countries to reach their potential, which is independent and has no relation with the pandemic.

The "learning period" included in the first scenario is modeled with a logistic function, where the output of the logistic function define the share of adoption of the WFH potential. It therefore starts with 0% in 2020, reaches 30% in 2030 and 90% in 2040. The choice of a logistic function is justified by the need of simulating lower initial shares of adoption and faster rates of adoption once the mechanism favoring WFH start acting, until "normal" mechanism dominate again and the rates of adoption decrease.

Second Method

As mentioned in the "Classification of Occupations" section, most of criticism surrounding Dingel and Neiman attempt to extend the SOC classification to the ISCO one relates to the diversity of jobs tasks around the world associated to the same job classification. This complicates the efforts of extending WFH statistics at world level. In particular, differences in the organization of production or in the level of technological adoption may imply more face-to-face interactions or physical task in poorer economies. As consequence, method 1 may results particularly inaccurate in predicting WFH shares for poorer economies (developing countries in this model).

A Policy Research Working Paper published by the World Bank in May 2020 [8] after recognizing the work done by Dingel Neiman proposes an alternative way to better grasps WFH drivers among countries. Jobs tasks do not vary at the occupational level, as in the SOC classification, but rather at the individual one. Some individual characteristics correlates better with the likelihood of being able to work from home. Skill surveys from 53 countries were analyzed and a new method for interpreting the questionnaire answers was chosen. Instead of adopting a binary method as DN, a continuous one was preferred, the higher the number of positive answers to criteria satisfying questions, the higher the probability of WFH. In this way the final measure can take a value from 0 to 100. The surveys used were the PIAAC (Program for the International Assessment of Adult Competencies) for 35 countries, mostly developed ones, the STEP (Skills Towards Employability and Productivity) for 15 developing countries and the LMPS (Labor Market Panel Surveys) for three countries in Middle East and North Africa. Data included employed individuals ages 16 to 64 years.

Cross country results: Results again confirm, as in method 1, the positive relationship between F2F task indexes and GDP per capita. Richer countries have less jobs physical/manual intensive, at contrary, they show higher intensity of jobs requiring F2F. Figure 3.7. Therefore two opposite forces are in place in defining the relationship between GDP and WFH. However, F2F occupations also tend to be more intensive in the use of ICT, and this factor reduces negative F2F effects on WFH probability. The World Bank paper show some differences from DN. However within country results are more useful to the purpose of this research and their outcomes were applied in EDGE.

Within country results: The availability in the PIAAC, STEP and LMPS datasets of data regarding gender, age and education of the respondents allowed for the inferring of correlations WFH-driver. Results show large disparities in WFH probabilities, in brief:

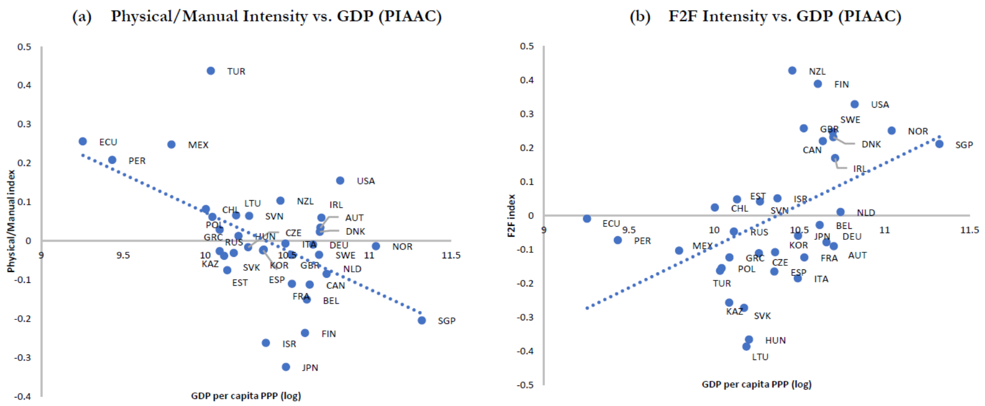


Figure 3.7. Cross Country results, World Bank

- Across countries, women are more likely to have teleworkable jobs. This emerges as consequence of their less presence in physical/manual job.
- Educational attainment also strongly favor WFH amenability, across all 53 countries college graduates are more amenable to WFH. This result was also found in DN. This effect was found to be the most impacting one.
- Older workers are less likely to have teleworkable jobs. Two counteracting forces are at play. In fact F2F intensity increases with age, while physical/manual intensity decreases with age. The first effect prevails.
- Last two drivers impacting WFH probabilities were related to job characteristics, namely Self-Employment (or not) and Formal and Informal status. However it was not possible to insert these two drivers in EDGE and therefore are not discussed.

These inferences are country group specific (PIAAC,STEP,LMPS) and are shown in the next page. Figure 3.8.

An implementation in EDGE followed these steps:

1. Extract population data from the International Institute for Applied Systems Analysis (IIASA) dataset reporting country specific projections up to 2100. This dataset provides information about gender, education and group age. [10]
2. Extract the coefficients as shown in the next page.
3. Bind the two data frame in a unique dataset having temporal, regional and SSP resolution.
4. Correct WFH values projected by method 1, therefore applying the interpolation function, with the "within country" coefficients found with method 2 and contained in the dataset produced in point 3.

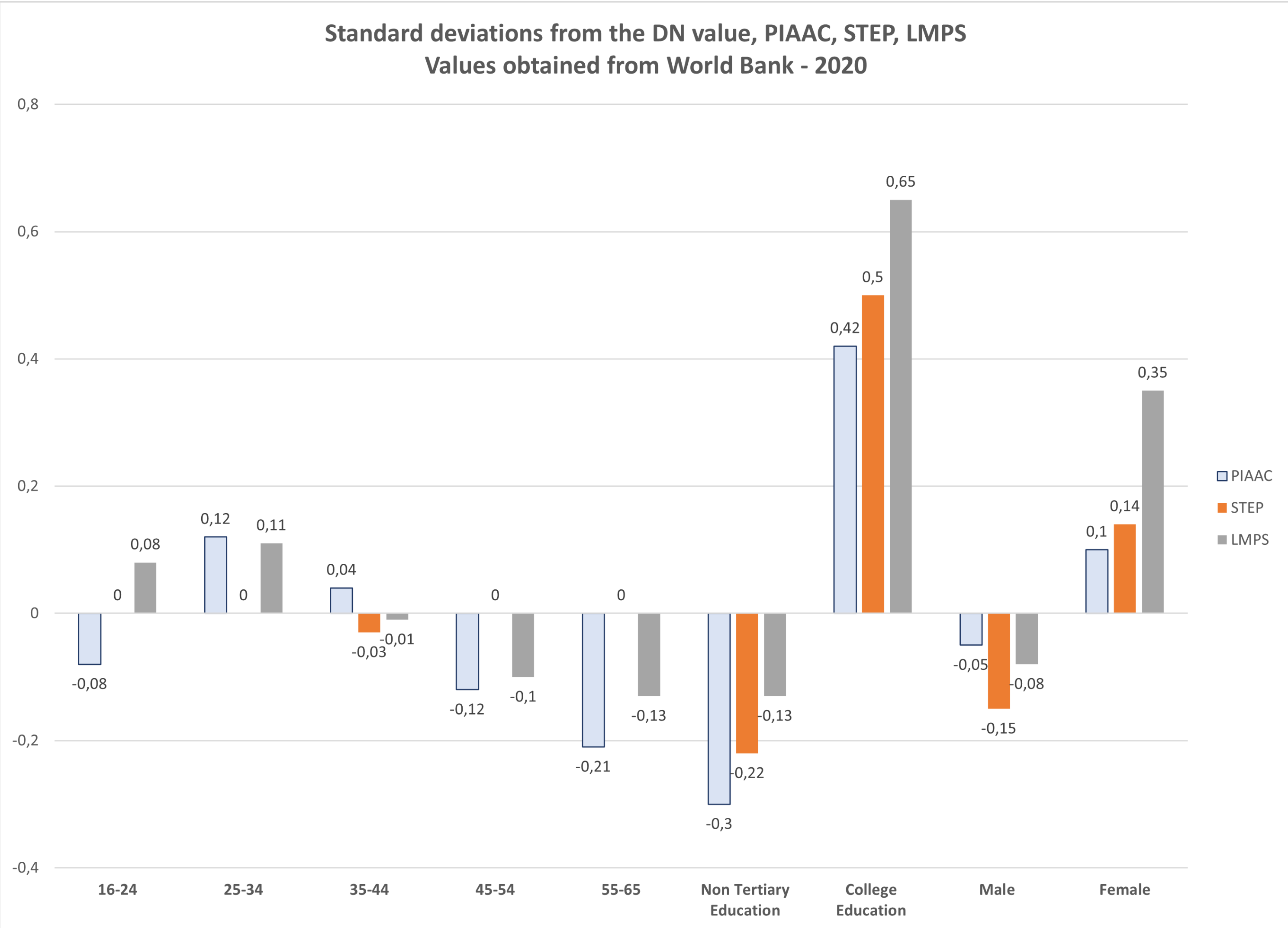


Figure 3.8. Method 2 Coefficients

Second Method, EDGE The importance of the dataset made available IIASA is crucial in this research, as it is used for two different purposes in the model. Data were produced in 2014 and published in a paper on "Global Environmental Change", "The human core of the shared socioeconomic pathways: Population scenarios by age, sex and level of education for all countries to 2100". [10] The advantage of this dataset is that it provides results ready to be used as inputs in EDGE, due to their grouping by SSP. The type of information it provides is the following:

Population|"Gender"|Aged"XX-YY"|"Type Of Education" |value|

"Gender" can be Male and Female, "Type of Education" can be No Education, Primary Education, Secondary Education and Tertiary Education, and age takes values from 15 to 64 with a time step of 4 years. Grouping education groups a part from Tertiary Education, the total number of combinations for a specific year is 40. They were reduced to 20 as the World Bank coefficients adopts the same year values from 16 to 65 but with an 8 years time step. Years span in EDGE (projections) from 2020 to 2100 and therefore values for this time range were extracted, with a time step of 5 years, which is also the one of EDGE. Values were also country and scenario specific for a total of around 330 thousand combinations.

"Within country" coefficients as found by the World Bank are expressed as standard deviations of the country group WFH mean. Calculating the mean of PIAAC countries' WFH was not possible, however their WFH interpolated values obtained from the method 1 function were not so different, due to their relatively similar GDP per cap. The choice was therefore to refer them to the WFH country specific coefficients. The formula implemented in EDGE is the following, where coefWFH is the new WFH potential level calibrated with method 2, value is the old WFH potential level from method 1, and "i" form 1 to 20 is the element of the calibration vector shown before.

$$coefWFH_{scen,reg,yr} = \sum_{i=1}^{20} value_{scen,reg,yr} \cdot coefSD_{reg,i} \cdot coefSSP_{scen,reg,yr,i} \tag{3.1}$$

coefSD is obtained from the World Bank inferences by applying this conversion:

$$coefSD_{reg,i} = 1 + \frac{1}{2} \cdot erf(\frac{coef}{\sqrt{2}}) \tag{3.2}$$

Where erf is the standard error function, coef is the corrected standard deviation of the mean taken by the World Bank. CoefSSP is instead obtained with this formula:

$$coefSSP_{scen,reg,yr,i} = \frac{population_{scen,reg,yr,i}}{population_{scen,reg,yr}}. \tag{3.3}$$

The "coef" corrected standard deviation of the mean is calculated considering that each age group (5) can be either Man or Female and can have a Tertiary o Non

Tertiary Education, for a total of 5x4 combinations. Their relative three standard deviations (Gender, Education, Age) were then summed.

Country mapping is shown in Figure 3.9 All countries had their pair in the IIASA dataset. However EDGE WFH coefficients calculated with method 1 were expressed in EDGE regions. Therefore multiple countries in World Bank were assigned to values in EDGE datasets (eg OCD countries), and then averaged to return a unique value for the region. Some regions in EDGE were not included in the World Bank surveys, it's the case of China, and were therefore not corrected.

Dataset	**Countries**	**Year**
PIAAC	Austria, Belgium (Flanders), Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russian Federation, Slovak Republic, Spain, Sweden, United Kingdom (England and Northern Ireland), United States	2011/2012
	Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia, Turkey	2014/2015
	Ecuador, Hungary, Kazakhstan, Mexico, Peru	2017
STEP	Bolivia, Colombia, Lao PDR, Sri Lanka, Vietnam	2012
	Armenia, El Salvador, Georgia, Ghana, Kenya, North Macedonia, Ukraine	2013
	Serbia	2015/2016
	Kosovo, Philippines	2015
LMPS	Tunisia	2014
	Jordan	2016
	Egypt	2018

Figure 3.9. Second Method regional mapping

3.1.5 Employment to Population Ratio

All WFH coefficients obtained so far are expressed as shares of Employed Population. EDGE equations however are expressed as function of population. A conversion was therefore needed to obtain the share of total population working at home. At this scope it was again consulted the IIASA dataset. The formula implemented in EDGE is the following:

$$WFH_{scen,reg,yr} = coefWFH_{scen,reg,yr} \cdot ETP_{reg} \cdot WP_{scen,reg,yr} \tag{3.4}$$

ETP is the Employment to Population ratio and is the greatest source of uncertainty in this equation. It refers to the share of Working Age Population (WP) employed. Data were obtained from the World Bank dataset and were country specific. [70] The average ETP values for the World in 2019 was of 57% and it had been declining constantly in the last 30 years, with a value in 1990 of 62,5%. Similar trends were presents at country level, however in this research it was chosen to average the last 30 years entries to a unique value and assume it constant throughout the century. The assumption is certainly strong, however last 30 years ETP trends show, on average, very small change in magnitude. The World ETP average declined of 9% in 30 years, at a constant rate of 0,3%/yr. Longer term ETP predictions were beyond the scope of this research and considered its relatively low influence on the model outputs the assumption was judged acceptable. It must be highlighted still, the collapsing of ETP of 5 percentage points in 2020 due to COVID19 pandemic, equivalent to 15 years of previous reduction.

Working Age Population (WP) is instead the share of population between 16-65 years old, and was obtained summing all respective values in the IIASA dataset.

3.1.6 WFH Potential Projections

In the next pages are shown the results of WFH implementation in EDGE. In a first page are shown the figure from 1 to 4, in a second those from 5 to 8. In a third are shown the share of WFH on total global population and in a fourth page projections up to 2100.

Table 3.1. List of Figures

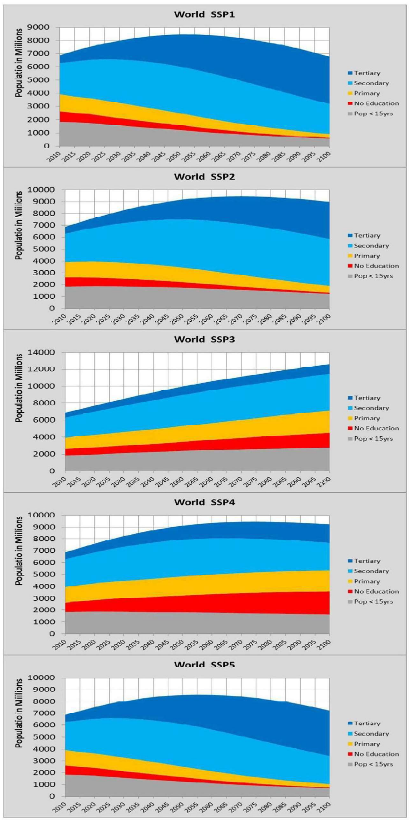
Number	Content
1	IIASA Scenarios
2	IIASA-EDGE Female and Tertiary Ed.
3	GDP pop
4	ETP*WP ratios
5	WFH potential, first method
6	WFH potential, second method
7	WFH % total population, first method
8	WFH % total population, second method
9	WFH % total population, globe, first method
10	WFH projections for 2100, first method

In order to clarify the reading of the graphs, the curves are evidenced in two colors, where blue stands for Developed Countries and Yellow for Developing countries. Table show the choice of the countries. Italy is also included separately for research purposes, as well as South Africa which was considered separately from Africa. For the sole purpose of plotting, European countries WFH results are averaged, while all flow calculations in the code (WFH and Energy) are European Country specific. A discussion of the results is performed in the next chapter.

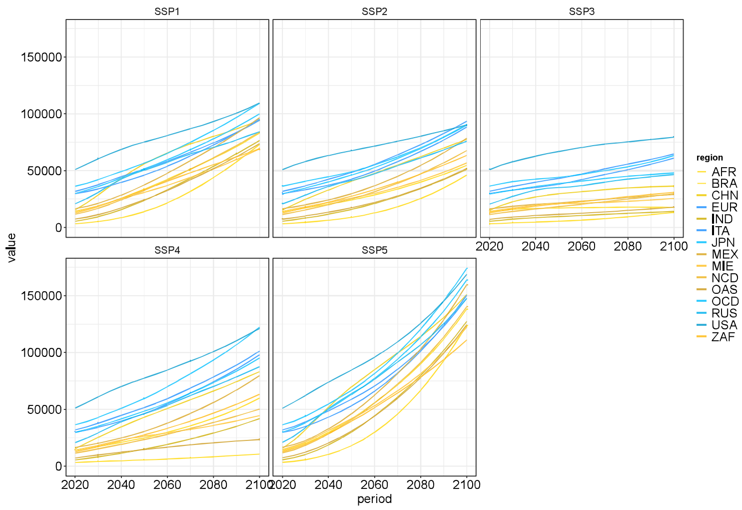
Table 3.2. Regions definitions

Developed	Developing
European Union EUR	Africa AFR
Italy ITA	Brazil BRA
Japan JPN	India IND
Other OECD OCD	Mexico MEX
Russia RUS	Middle East MIE
United States USA	Other Non OECD NCD
	Other South and Asia OAS
	South Africa ZAF

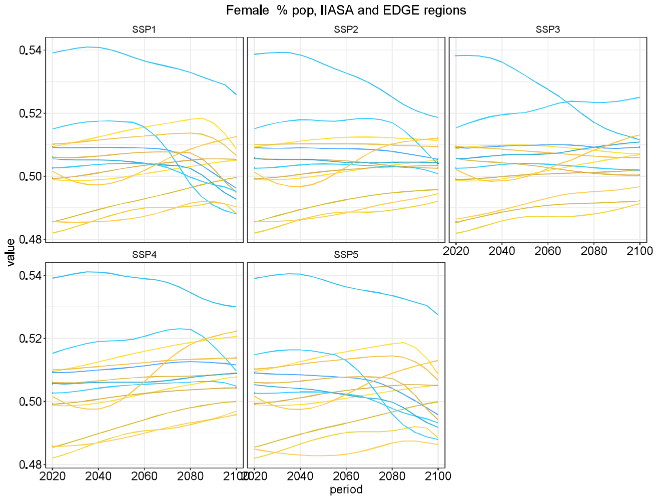
S. KC, W. Lutz / Global Environmental Change 42 (2017) 181–192 189



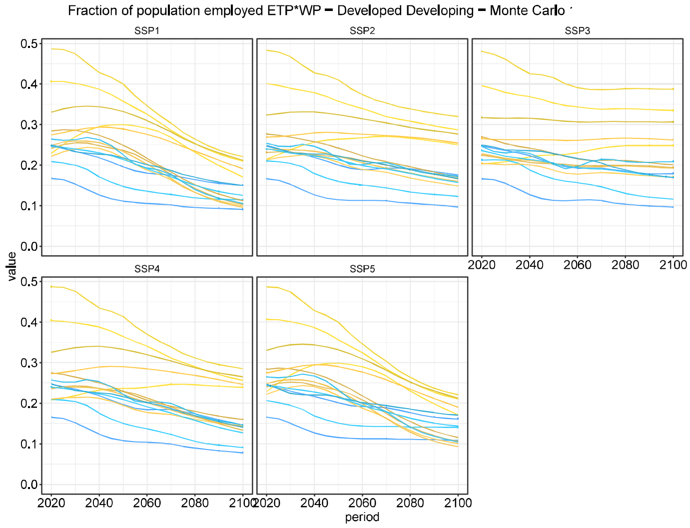
gdppop Developed Developing



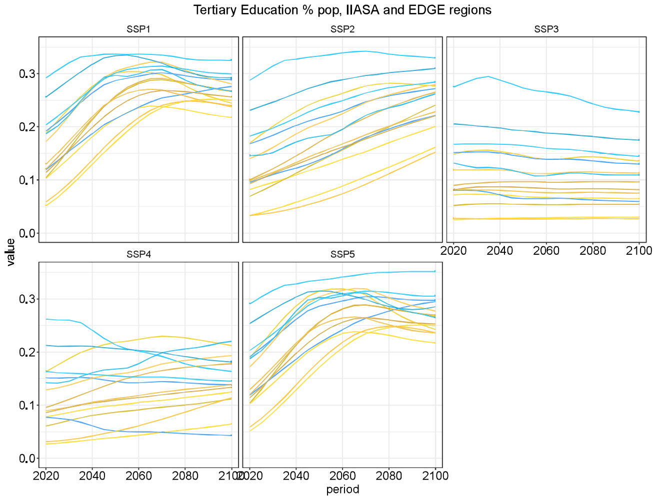
Female % pop, IIASA and EDGE regions



Fraction of population employed ETP*WP – Developed Developing – Monte Carlo

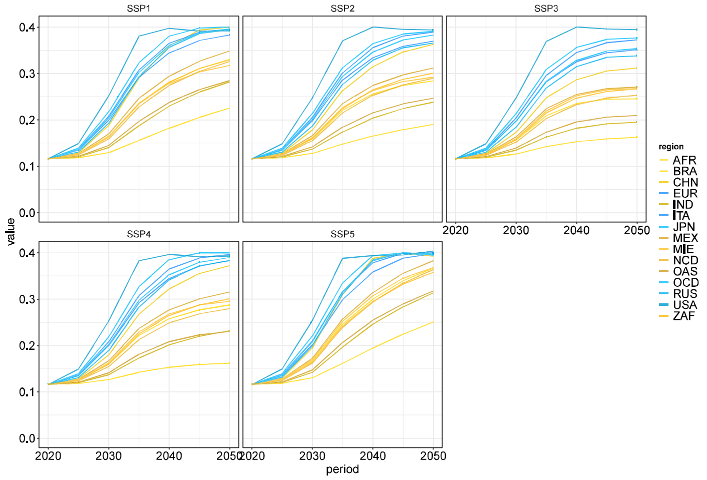


Tertiary Education % pop, IIASA and EDGE regions

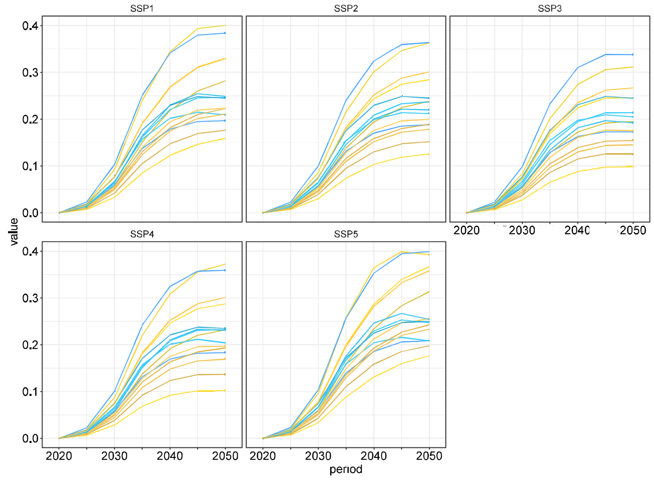


2050 PROJECTIONS

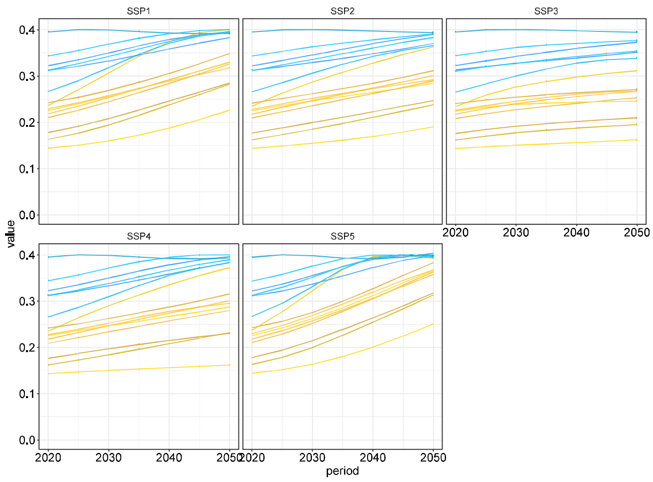
WFH potential % employed persons, Developed Developing DINGEL NEIMAN (mean)



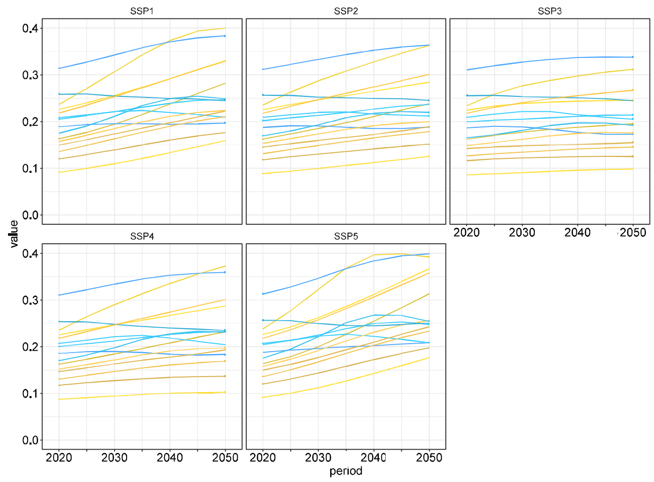
WFH potential % employed persons, World Bank



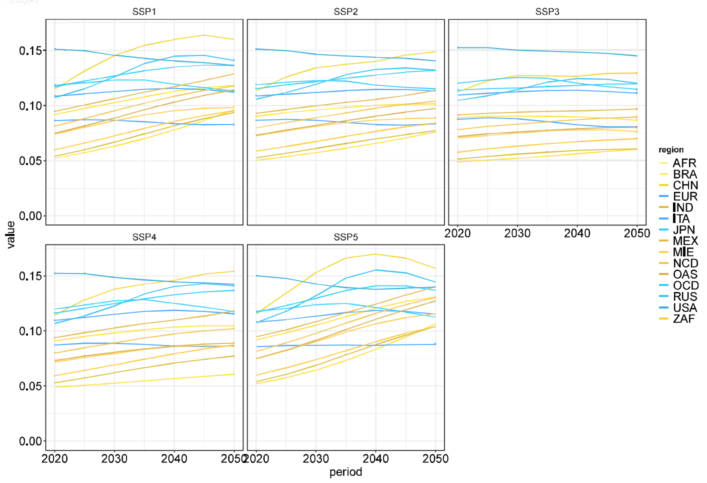
WFH potential % employed persons, Developed Developing DINGEL NEIMAN (mean)



WFH potential % employed persons, World Bank

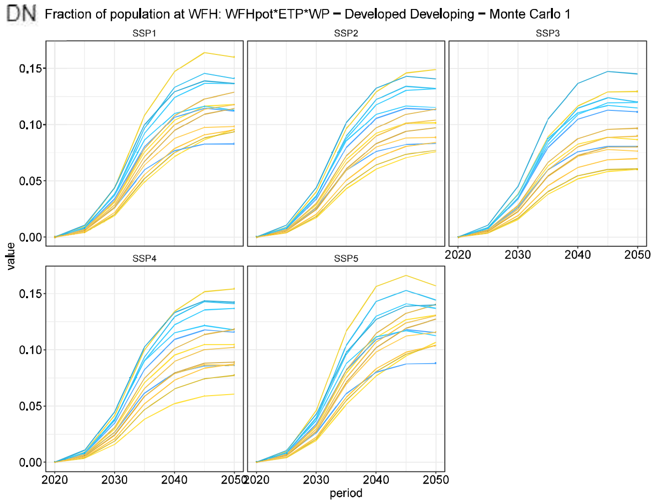


DN Fraction of population at WFH: WFHpot*ETP*WP – Developed Developing – Monte Carlo 1

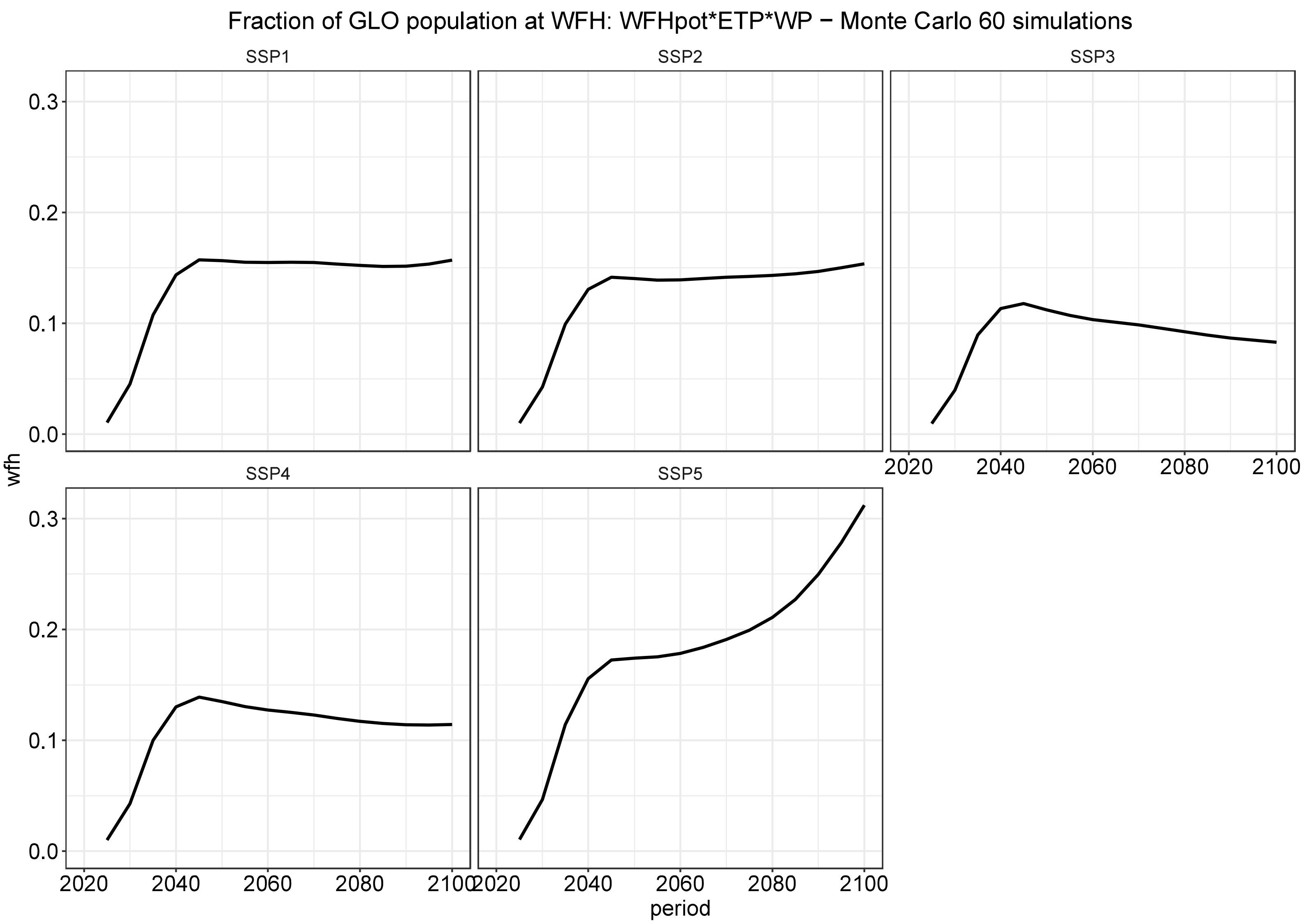


WB Fraction of population at WFH: WFHpot*ETP*WP – Developed Developing – Monte Carlo 1

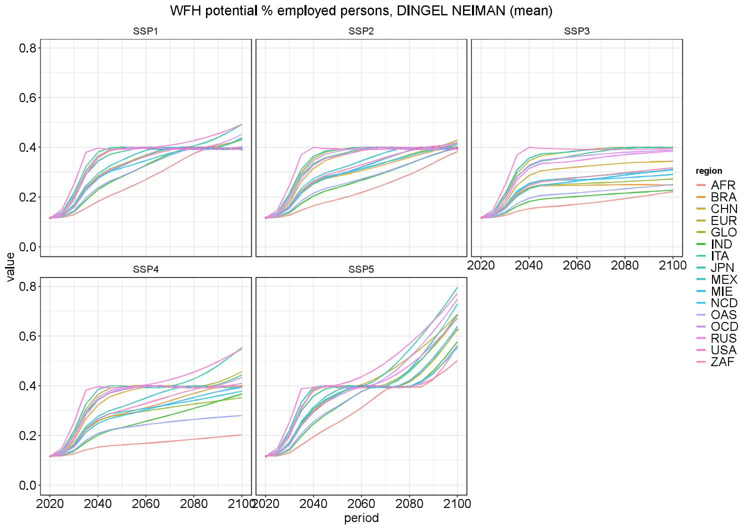
DN Fraction of population at WFH: WFHpot*ETP*WP – Developed Developing – Monte Carlo 1

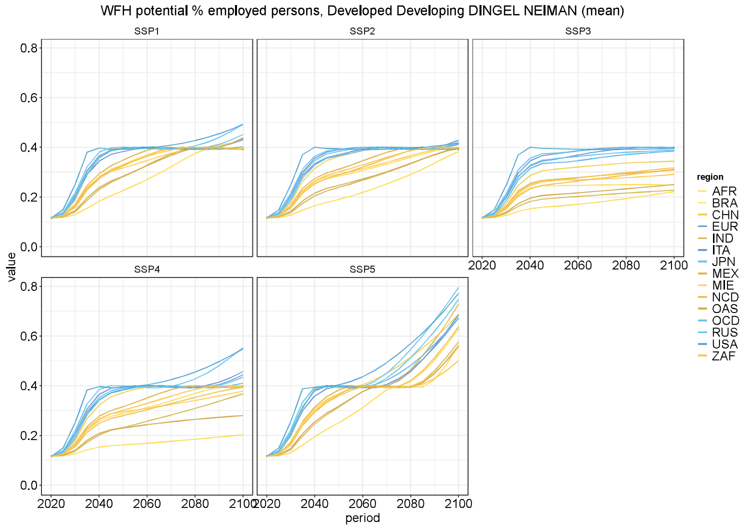


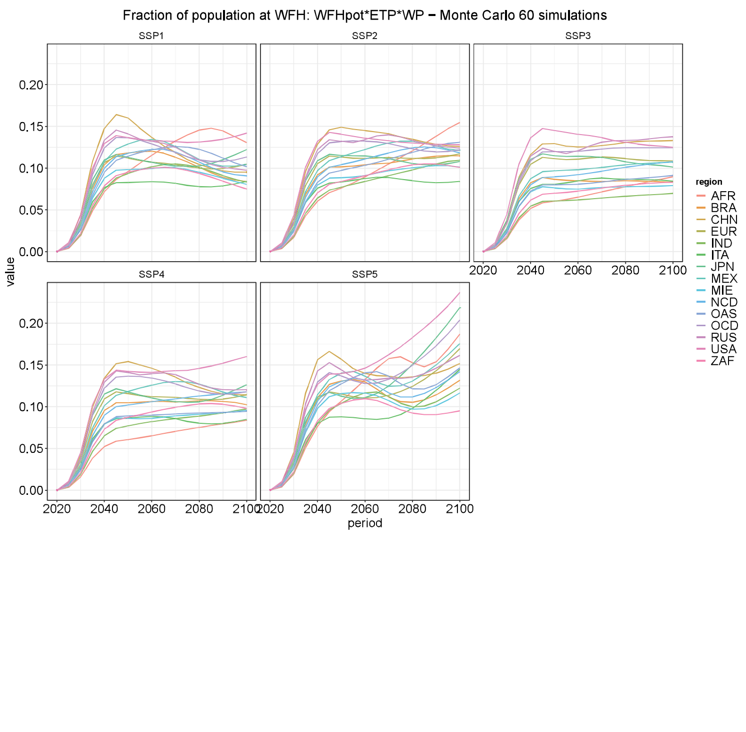
WB Fraction of population at WFH: WFHpot*ETP*WP – Developed Developing – Monte Carlo 1

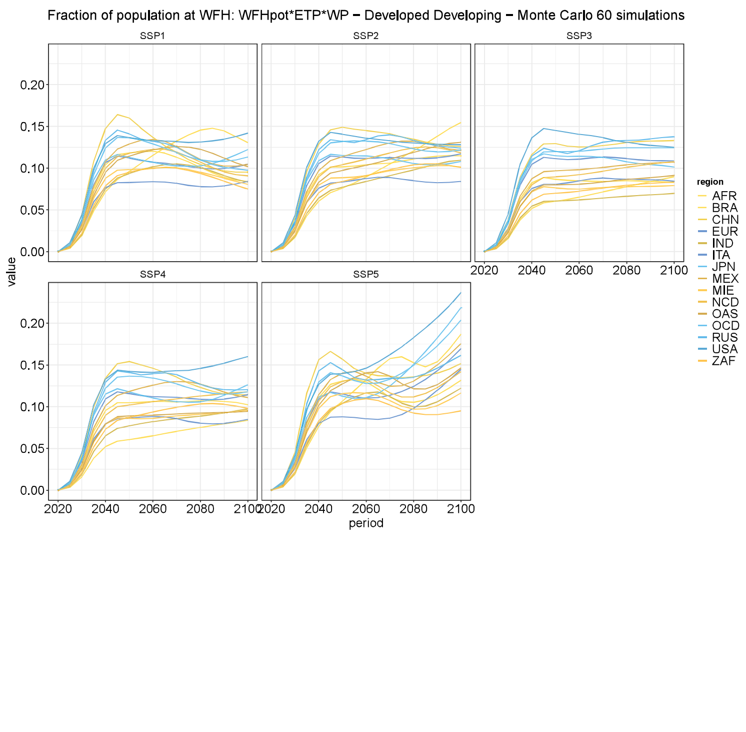


Fraction of GLO population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
wfh
period
0.0
0.1
0.2
0.3
2020
2040
2060
2080
2100


WFH potential % employed persons, DINGEL NEIMAN (mean)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period
region
AFR
BRA
CHN
EUR
GLO
IND
ITA
JPN
MEX
MIE
NCD
OAS
OCD
RUS
USA
ZAF


WFH potential % employed persons, Developed Developing DINGEL NEIMAN (mean)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period
region
AFR
BRA
CHN
EUR
IND
ITA
JPN
MEX
MIE
NCD
OAS
OCD
RUS
USA
ZAF


Fraction of population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period
region
AFR
BRA
CHN
EUR
IND
ITA
JPN
MEX
MIE
NCD
OAS
OCD
RUS
USA
ZAF

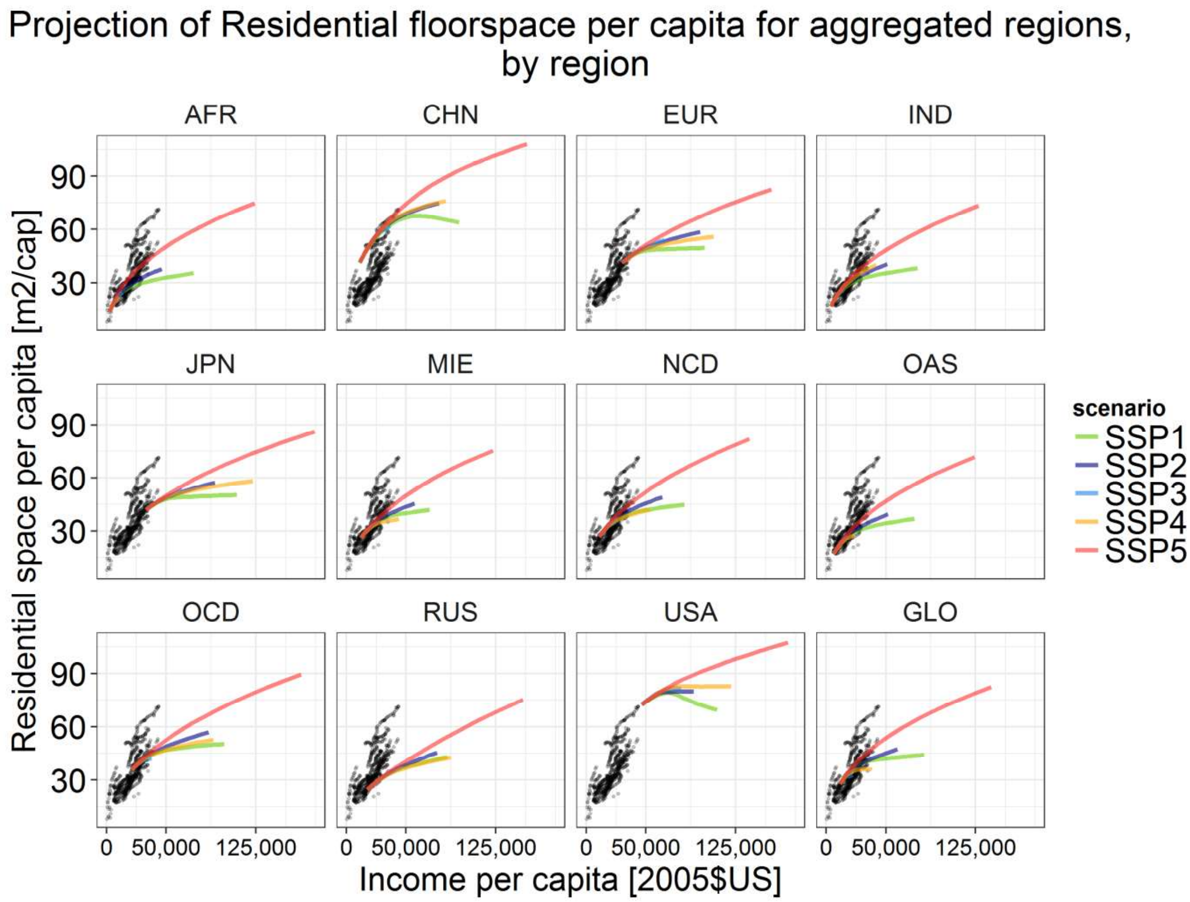

Fraction of population at WFH: WFHpot*ETP*WP − Developed Developing − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period
region
AFR
BRA
CHN
EUR
IND
ITA
JPN
MEX
MIE
NCD
OAS
OCD
RUS
USA
ZAF

3.2 Commercial Separation

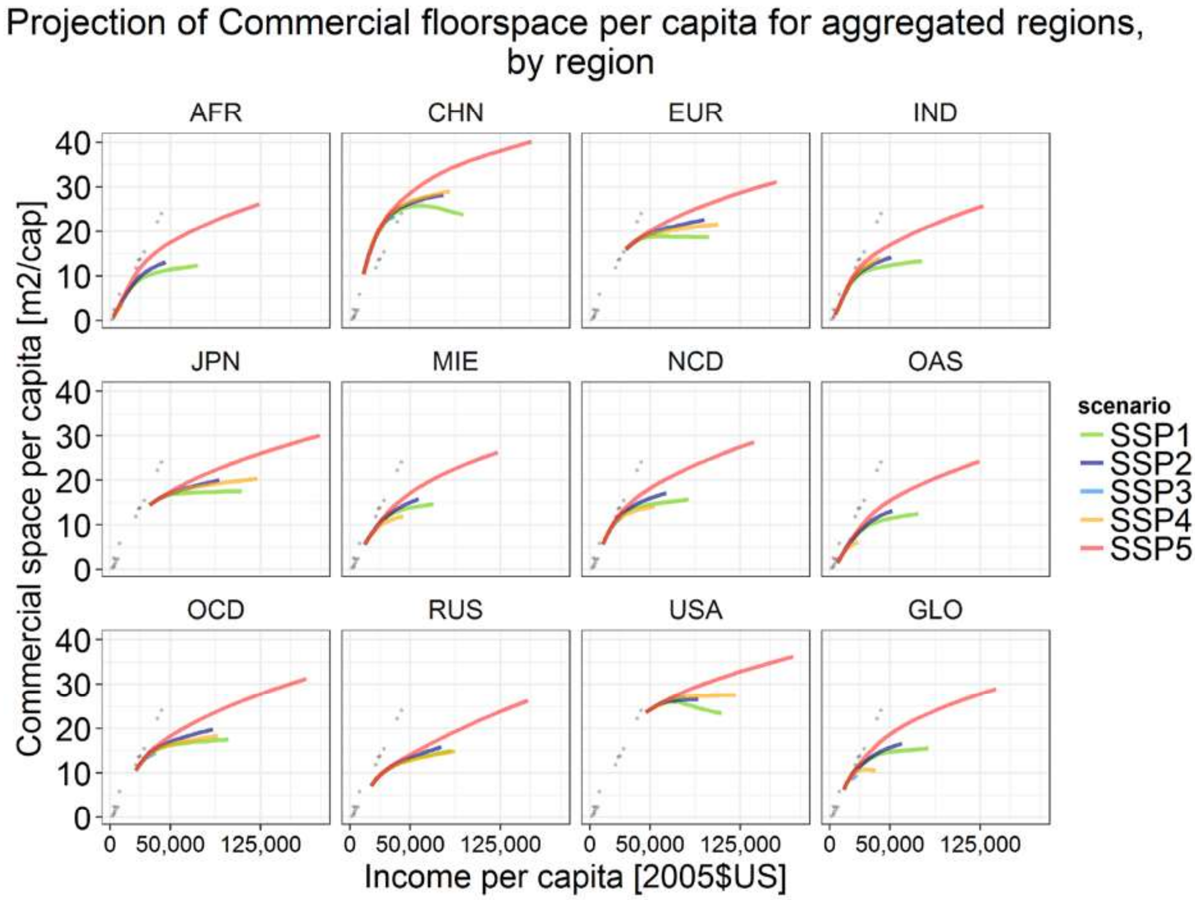
3.2.1 EDGE, overview of commercial sector

As was mentioned in Chapter 2, EDGE model through is coding is not able to diversify outputs between Commercial and Residential projections. Total Final Energy as well as all others indicators are computer for the Building Sector as a whole. However for the purposes of this research such separation was crucial, because early data were suggesting two counteracting forces taking place, related to the same phenomena. WFH would increase consumptions in the residential sector but decrease those of the commercial one. Of course, net effects would not only depend on the absolute magnitude of changes but also, and mainly, on the shares on total Building energy consumption of the two sectors. To clarify, if commercial final energy consumption is 30% of total Building final energy consumption, even a stronger than residential reduction in consumption would rarely imply net negative effects on the total.

EDGE takes in consideration the commercial sector by summing its projected floor space to the residential one, and then compute energy demands by including total floor space F in the equations requiring it. Namely “Space Heating” and “Space Cooling”. Residential floor space is obtained through the definition of the equation descripted in chapter 2 and its calibration (income and population elasticities) on historical data. Commercial floor space calibration in EDGE is performed by retrieving data from the IEA 2014 “Tracking Clean Energy Progress” dataset. [71] Data in this dataset are available for the US, EU, China, India, OECD, OAS and NCD relative Commercial and Residential 2011 floor space. The calibration is then performed by EDGE and the resulting interpolation is shown in Figure 3.10 . The trend is similar to the one found in this research for the WFH coefficient, with developing economies showing higher rates of increase in commercial shares and developed countries leveling off around values of 35% independently from the GDP per capita. The non linear regression is performed by EDGE with a “Non Linear Gompertz Growth Model”. (An almost identical regression was obtained applying the Generalized Additive Model used for the WFH regression). In the next page are shown floorspace and commercial floorspace predictions in EDGE, SSP specific.



Projection of Residential floorspace per capita for aggregated regions, by region
AFR
CHN
EUR
IND
JPN
MIE
NCD
OAS
OCD
RUS
USA
GLO
Residential space per capita [m2/cap]
90
60
30
0
50,000
125,000
Income per capita [2005$US]
scenario
SSP1
SSP2
SSP3
SSP4
SSP5



Projection of Commercial floorspace per capita for aggregated regions, by region
AFR
CHN
EUR
IND
JPN
MIE
NCD
OAS
OCD
RUS
USA
GLO
Commercial space per capita [m2/cap]
40
30
20
10
0
50,000
125,000
Income per capita [2005$US]
scenario
SSP1
SSP2
SSP3
SSP4
SSP5

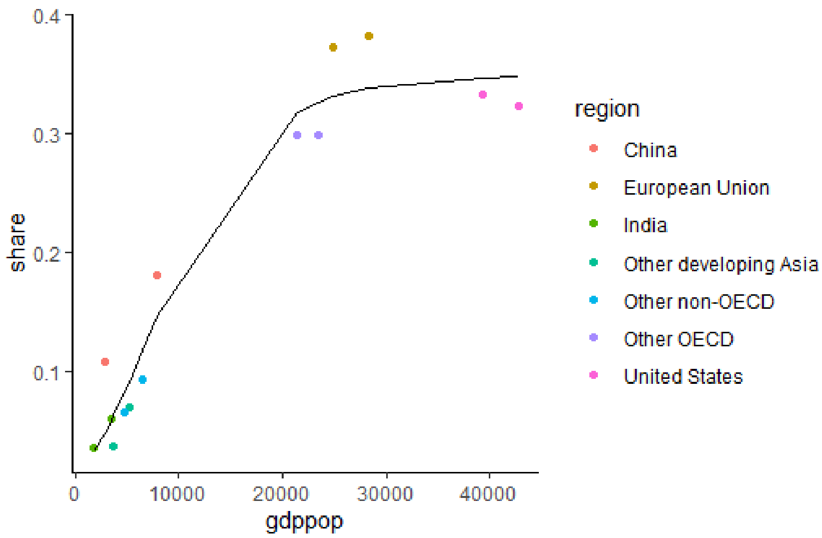


Figure 3.10. Calibration of commercial floorspace

3.2.2 Data retrieving

In this research it was required an End Use level detailed separation between commercial and residential sector. Data and drivers already implemented in EDGE were not sufficient to provide reliable projections for commercial consumption patterns. A considered approach was the separation of the End Uses equations by using the floor space shares, corrected with some calibrations. However this would have implied assigning a direct relationship between floor space shares and energy consumption commercial/residential shares. Moreover, some equations in EDGE are not related to floor space and therefore a forced relationship may have led to great errors in final results. It was hence chosen to make use of the IEA "Energy Technology Perspective" (ETP) of 2017, [19] which provide data for End Use consumptions both for the residential and commercial sector, at IEA Regions level. It was then performed the calculation of the shares.

IEA ETP 2017 provides three future scenario, named "Reference Technology Scenario" (RTS), "Two Degree Scenario" (2DS) and "Beyond Two Degree Scenario" (B2DS). Data were retrieved for all three IEA scenario, however, a simple "manual" sensitivity analysis showed very little variations in the shares and it was thus decided to keep only the RTS Scenario in the model. Additionally, merging RTS with SSP scenario has a logic, that may be undermined by the use of the 2DS or B2DS.

IEA Reference Technology Scenario takes into account today's commitments by countries to limit emissions and improve efficiency. NDCs as submitted in the Paris Agreement are also considered. RTS is not thus a Business as Usual scenario, as it represents already a major change from historical trends. It needs substantial accelerations in policies all over the world for greater pledges in emissions reductions. IEA states that if successfully adopted, these efforts would likely result in an average temperature increase of 2,7°C by 2100. 2DS and the B2DS instead are implemented with technology improvements pushed to their maximum practicable limits so to achieve net zero emissions by around the mid of the century (2060). It must be highlighted again that the only intakes from IEA models in this research were the Residential FC shares, and most noticeably the fact that they did not vary much between IEA scenarios. This means that drivers of Residential shares do not vary with the various IEA scenario' assumptions, thus reducing the probabilities of IEA-SSP incompatibilities.

IEA has its own IAM, enabled with different sub models specialized in a particular sector. The End Uses shares introduced in EDGE were derived from the IEA's "Useful Energy Demand" block. The main difference with the EDGE model is the detailed characterization of the Commercial Sector and of its specific End Use drivers, allowed by IEA's capability of retrieving official data from national energy agencies. However also IEA states that the availability of historical trends for the Building sector was scarce, thus they also relied on multilinear regressions based on GDP, GNI per capita, urbanization and electrification rates to fill gaps in data, mostly confined to developing countries. The projection of Space Heating and Space Cooling demand, per unit of floor area and specific for the residential and commercial sectors, is made basing on estimations of buildings stock characteristics and building end use technologies. Buildings were broken down into three categories, near-zero energy buildings, buildings in compliance with energy codes and buildings without coding. A similar break down was made for building end use technologies. This methodology was then applied to estimate historical trends, calibrate regressions and project future demands. Three main adjustments were made prior to the calculation of the shares:

- IEA Regions did not coincide with EDGE ones, a matching was needed
- IEA time range extends up to 2060 while EDGE needed inputs for up to 2100.
- IEA considers separately Appliances and Lighting while EDGE binds them together.

Regional Mapping: In table is shown the adopted mapping, IEA 2017 dataset did not report explicitly data for Africa and thus the choice was to assign the continent the world average.

Time range: time span was extended up to 2100 by using a "Holt's Linear Trend Method" (1957) and manually correcting those trends which showed unwanted patterns. In order to provide the Holt algorithm with a sufficient set of datapoints, shares' data were artificially increased in resolution, increasing time span from 5 to 1 year. The interpolation was performed through spline regressions, using exact cubies with the method of Forsythe, Malcolm and Moler (1977). [72]

"Holt" method is implemented in R within the package "forecast". [73] It was chosen for the prediction of shares due to their smoothness and relatively high linearity (in the trends). However, due to its tendency to over-forecast, it was adopted a damped trend method (Gardner, McKenzie 1985) with a phi smoothing parameter equal 0.95. Still, trends for Space Cooling shares of NonOECD, ASEAN, Brazil and Mexico were still exhibiting apparent over-forecasting trends and their phi parameter was thus

Table 3.3. Regional Mapping

EDGE	IEA
European Union	European Union
Unites States	United States
China	China
Brazil	Brazil
India	India
Russia	Russia
Mexico	Mexico
South Africa	South Africa
OCD	OECD
Japan	OECD
MIE	World
OAS	ASEAN
NCD	NonOECD
Africa	World

corrected to 0.8. The choice of high damping parameters may produce paradoxically too conservatives trends, in particular for the share of Space Cooling.

Appliances and Lighting: The computation of shares was done by dividing Final Energy Consumption of the residential sector by Final Energy Consumption of Building sector as a whole. In order to bind together Appliances and Lighting shares in EDGE, it was followed this formula, where all index "share" refers to the share of residential consumption on the total and FC is Final Energy Consumption:

$$shareAL = \frac{share_{appliances} \cdot FC_{appliances} + share_{lighting} \cdot FC_{lighting}}{FC_{appliances} + FC_{lighting}} \tag{3.5}$$

3.2.3 Shares, results

First is presented a table in the next page summarizing the obtained shared for EDGE regions for the year 2020, 2050 and 2100. Values for 2020 and 2050 are calculated directly from the IEA dataset, while values for 2100 are obtained through the method introduced in the previous section. It follows a brief analysis of the results and in the last section part are shown the relatives graphs, first with a 2050 time span and then a version extended up to 2100.

Table 3.4. EU shares, results

Region	Year	AL	SC	SH	WH
	2020	49	40	66	84
AFR	2050	52	66	64	79
	2100	57	74	62	73
	2020	43	18	12	93
BRA	2050	44	51	2	91
	2100	49	67	0	88
	2020	74	52	65	88
CHN	2050	68	65	71	78
	2100	66	67	70	70
	2020	61	13	71	66
EUR	2050	42	12	68	65
	2100	40	13	66	62
	2020	41	74	38	93
IND	2050	66	92	28	82
	2100	73	93	23	68
	2020	57	29	69	70
JPN	2050	37	29	67	69
	2100	36	34	66	67
	2020	49	23	55	74
MEX	2050	37	62	45	68
	2100	29	73	40	66
	2020	62	40	66	84
MIE	2050	53	66	64	79
	2100	57	74	62	73
	2020	57	53	63	90
NCD	2050	65	78	60	83
	2100	67	87	58	76
	2020	41	50	33	93
OAS	2050	52	76	29	88
	2100	47	78	26	82
	2020	56	29	69	70
OCD	2050	37	29	67	69
	2100	35	34	66	67
	2020	40	33	78	82
RUS	2050	43	17	72	74
	2100	40	18	72	71
	2020	46	34	70	72
USA	2050	36	29	69	72
	2100	35	31	67	70
	2020	50	15	43	85
ZAF	2050	50	60	40	85
	2100	58	75	41	86

Appliances and Lighting (AL): Residential sector account for around 75% to 50% of Building energy AL FC in developing countries. Developed countries instead have shares between 50 to 40%, and thus a greater prevalence of AL in the commercial sector. Trends for Developing countries are different for two groups. A first group composed by three countries included China and India converge increasing toward values of 70% in 2100, a second included MIE and OAS converge decreasing to values of around 50% in 2100. Developed countries instead all show a decreasing tendency towards values of 40% by 2050 and to remain stable until 2100%. Within AL FC, Lighting accounts for around 20 to 30% of consumptions, while Appliances for 70 to 80%.

Cooking (CK): Cooking was modeled by IEA as present only in the residential sector, it is certainly a simplification but it was decided to keep this assumption also in EDGE, as the type of commercial sector analyzed is certainly restricted to subsectors where cooking End Use has not related FC. (eg. offices).

Space Cooling (SC): Space Cooling trends are strongly diversified between developing and developed countries. Countries like Russia and US decline from values of around 33% in 2020 to values of 18 and 30% in 2100. EU remains stable at values of about 10%. Developing countries instead show net increases, as is the case for MIE and Africa region, which rise both from 40 to 74% (modeled from the World IEA region). China rises from 50 to 70% in 2100 while India from 70 to 90%. IEA projections for developing countries Space Cooling showed a strange behavior from 2050 to 2060, with first a declining trend and then a new rise close to 2060. The Holt's forecasting algorithm interpreted this behavior as a temporary fluctuation and assigned increasing values up to 2100. As projected by IEA thus, space cooling residential shares are to increase constantly throughout the century.

This behavior is coherent with the one projected in EDGE through the equation descripted in chapter 2. Overall cooling demand is dependent on income per capita, with the effects of marginal income being high for medium income levels and on a "Climate Maximum" which depends on the number of CDD in a region. It was not possible to asses whether or not IEA model includes Climate Change (CC) feedback in its coding (the IAM code is kept private), however, independently from CC the Climate Maximum of mid latitude regions-developing countries is higher than the one of high latitudes-developed countries. CC, if not considered by IEA, would augment the increasing trend by increasing CDD.

Income levels are projected to increase substantially in developing regions, particularly in the first half of the century. An increasing share in residential cooling, signals that the increasing shares of commercial floor space are not sufficient to balance the net increase in residential cooling. Indeed commercial floor space shares of developing regions should increase with greater rates in the first half of the century, if the calibration found in EDGE for commercial floor space shares holds true also in the IEA models. The three forces identified for developing regions are thus the following:

- A negative force due to increasing shares of commercial floor space.

- A positive force due to the reaching of Climate Maximum, which should though affects both residential and commercial cooling demand.
- A positive force due to increasing GDP per capita. Cooling demand will rise accordingly to GDP both in residential and commercial sector.

The trend for residential demand is therefore explained by a greater impact of GDP per capita and Climate Maximum on residential demand than on commercial demand. This could be so explained:

- Commercial cooling demand is less dependent from GDP per capita, it is likely than even in regions with overall low income per capita levels, commercial standards and regulations lead to an adoption of conditioners in work spaces, offices etc. Hence, commercial cooling demand reaches early saturation levels.
- Residential cooling demand on the contrary is likely to be more dependent on income per capita, or purchasing power, of people/customers.

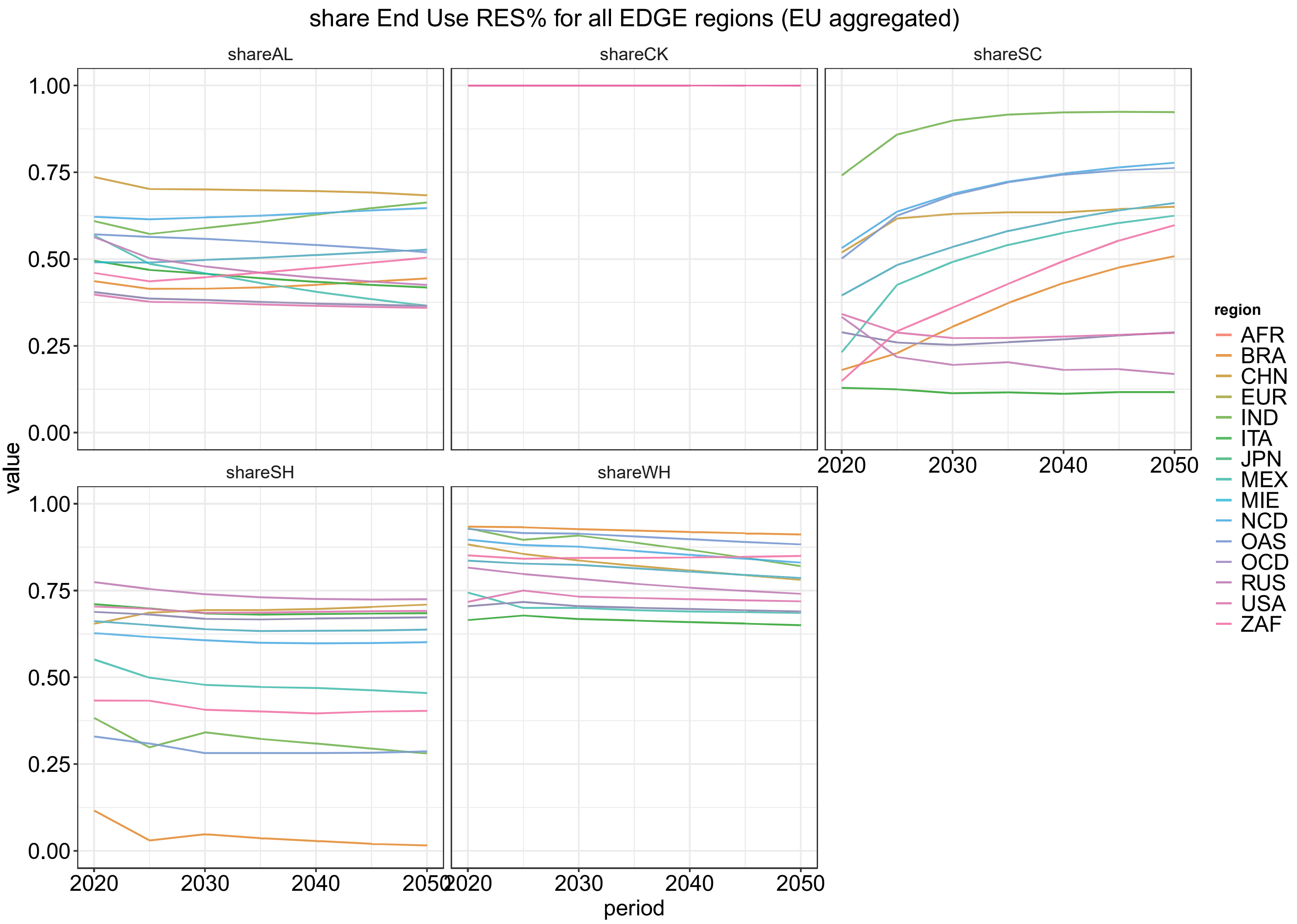
The higher shares of commercial space cooling in developed countries are therefore probably explained by higher shares of commercial floor space (they should level off around 40%) and lower CDD and Climate Maximum.

Space Heating (SH): Overall, shares are projected to decrease of a few percentage points for all regions throughout the century, with some developing regions experiencing greater trends, as is the case for India, which decreases from values of 38% in 2020 to 23 in 2100%. Also India show a decrease from values of 12 to 0. In general mid latitudes countries show a net shift in Space Heating from residential to commercial. This trend confirm the hypothesis that IEA models already include CC feedback effects. An expected decrease in HDD due to CC should indeed contribute to a reduction on residential heating demand, while the commercial sector is probably less sensitive than the residential to HDD (and CDD).

Water Heating (WH): Water Heating trends are also decreasing for most countries, with levels for developing countries being from 75 to 90% while those of developed countries from 60 to 75%. India in particular is projected to decrease from 93% in 2020 to 70% in 2100. This trend could be explained again by CC effects on the demand, with higher temperatures leading to lower heating needs in residential and a lower sensitivity of commercial/public sector on external temperature profiles. As example, water heating needs of an hospital are mostly independent from external temperature profiles, being more related to sanitation needs (eg boilers to sterilize equipment, washing machines etc.).Summarizing three main considerations regard residential end uses can be made:

- Cooking and Water Heating show the greatest shares, respectively of 100 and around 75% (rough estimates).
- Appliances and Lighting is the End Use most balanced in share between residential and commercial, with world (rough) averages around 50%.

- Space Cooling and Space Heating show the greatest variations in magnitude between developing and developed countries, with higher shares of space cooling and lower shares of space heating for developing countries.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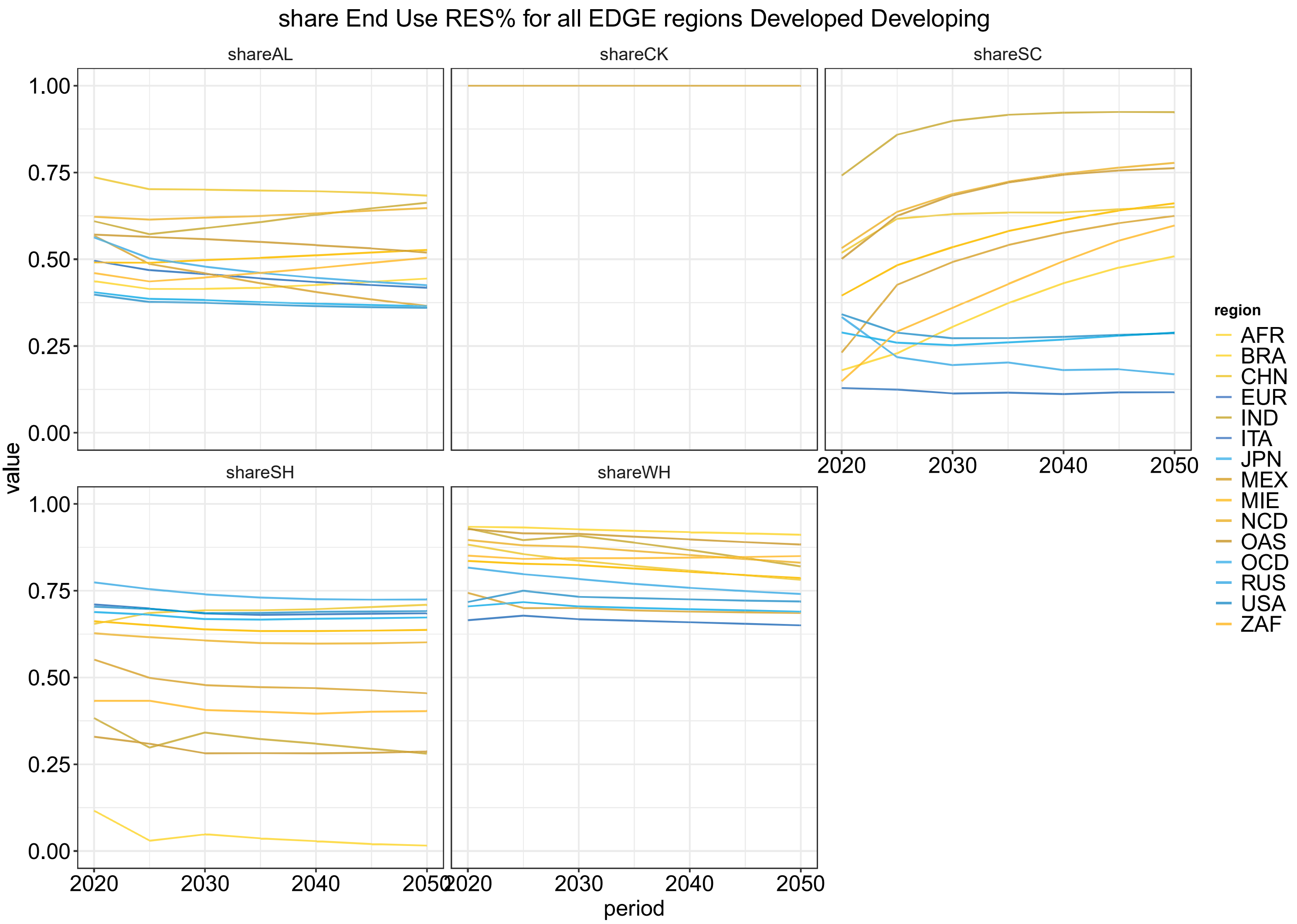
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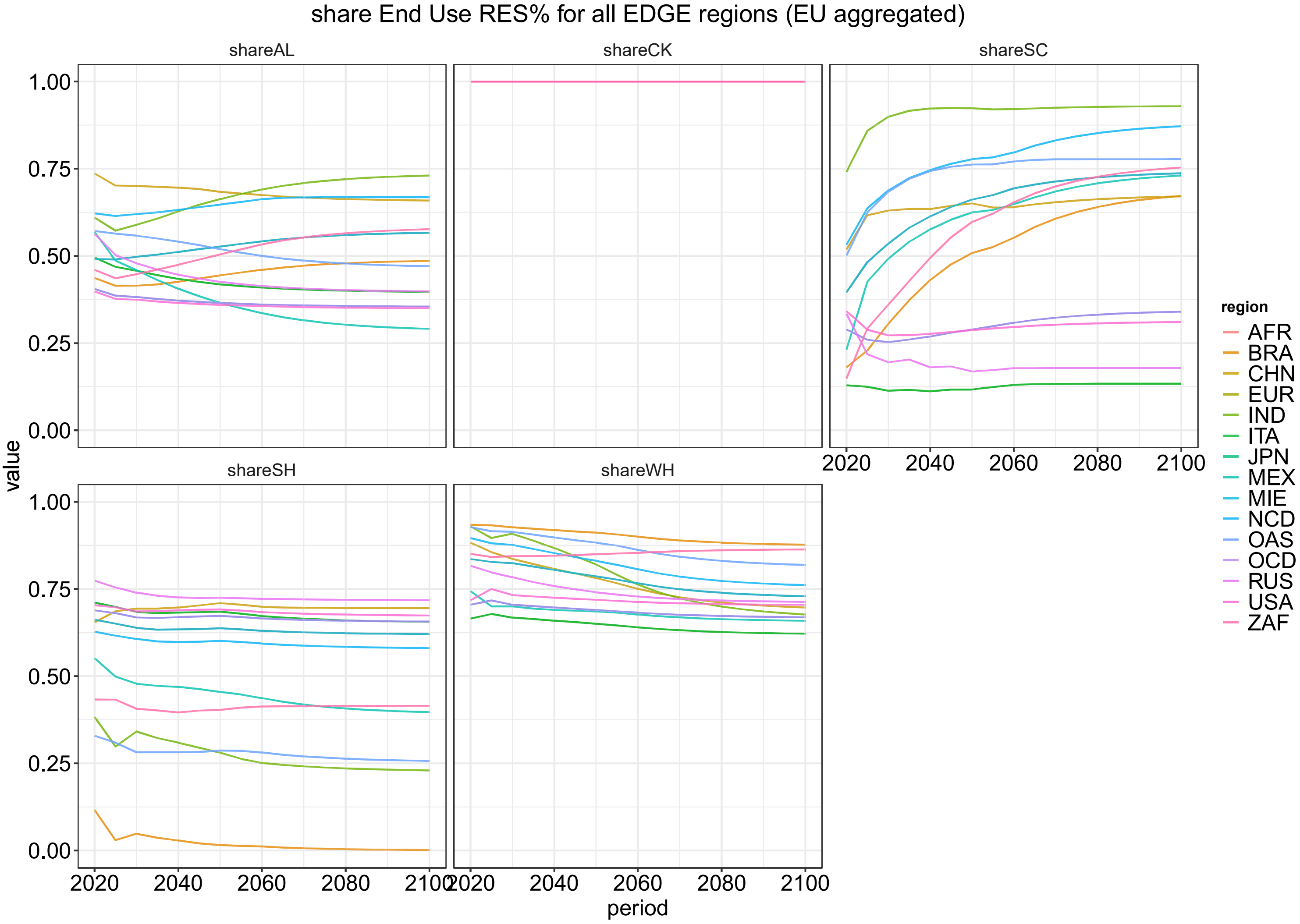
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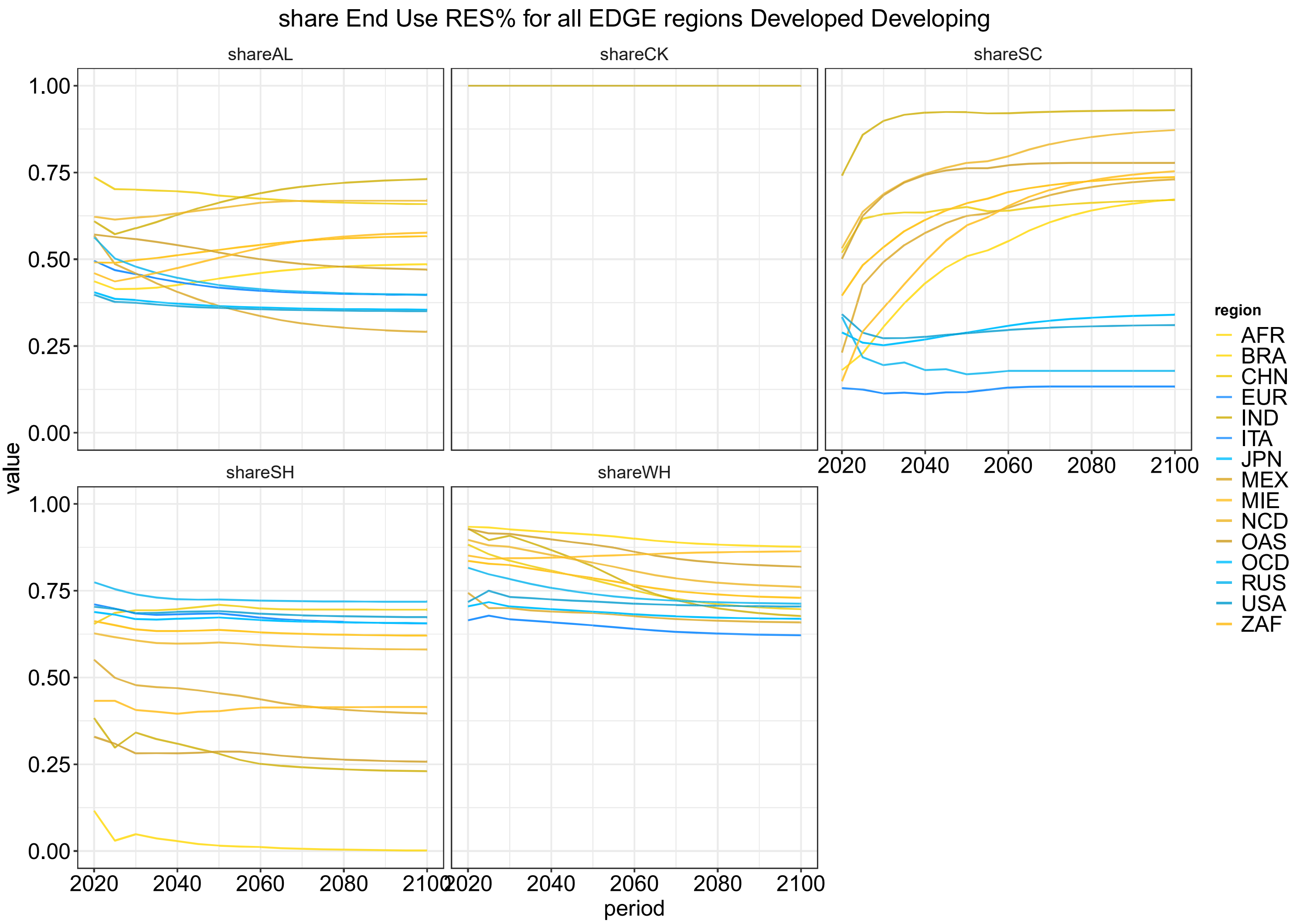
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3.3 Subcommercial separation

3.3.1 Introduction

The splitting of End Use equations in a residential and commercial part was not sufficient to perform analysis on WFH penetration in the Building sector. The model needed a parameter that could relate the shares of WFH to the relative energy consumption reductions of the commercial sector. However, not all commercial sub sectors are amenable to teleworking, as was introduced in the WFH section. Some jobs may require more physical and F2F tasks while others may totally be teleworkable. Moreover the calibration for commercial energy reductions in relation to WFH was made with data relative only to some subsectors, as is explained in the next section.

Hence, the commercial part of the End Use equations had to be split in two parts, through a coefficient, equal for all five equations, that accounted for the share of commercial sector final energy consumption subjectable to WFH. To clarify, let's assume 100 the FC of commercial sector, 50 the amount related to Hospitals, Food Retail and Hotels and 50 the one related to Public sector and Offices. Let's assume the average WFH probability for Hospitals, Food Retail and Hotels of around zero, while the one for Public and Office substantially higher. The WFH probability of zero for the fist group is considered structurally zero, this mean that those sectors will never be teleworkable. Instead the averaged WFH probability of the second group may vary in the future, with the correlation found between WFH potential and GDP per capita. In this ideal case, the coefficient for subcommercial separation would be 0,5 or 50%. Fluctuations in commercial energy demand due to WFH will therefore affect only the WFH energy related part.

3.3.2 Calibration

Data reporting sub commercial energy consumptions are scarce, even European databases do not offer a comprehensive collection for all EU countries. For example, it was not possible to find data for Italy, even in old datasets. Data were found for the United States, Singapore, India, European Union, Australia and China. The most important dataset for this research (and most cited in literature found) was the United States one, because it offered an almost direct linkage to the methodology adopted by Dingel Neiman in their WFH work. The method applied to the US dataset was then extended to the others found.

United States

Data for the United States were available in the Energy Information Administration (EIA) "Commercial Buildings Energy Consumption Survey" (CBECS) database. [20] In this database, buildings are classified according to the principal business, commerce or functions performed. In table is shown the CBECS classification, and some sub categories are shown if the definition of the commercial sub sector is not clear:

Table 3.5. CBECS classification

Building Type	Definition	Sub categories
Education	Academic or technical classroom	Schools, Universities
Food Sales	Retail or wholesale of food	Grocery, food market
Food Services	Preparation and sale of food	Bar, restaurant, catering
Health Care	Treatment facilities	Hospitals, medical offices, clinics
Lodging	Accommodation, residential care	Hotels, retirement home, convents
Mercantile	Sale of goods, shopping malls	Retail stores, malls.
Office	Office space, administrative	Gov office, administrative
Public	Law and order, recreational	Jails, Police stations, culture
Religious	Religious activities	
Service	All but not food or retail sales	Repair shop, car wash, barber
Warehouse and Storage	Store goods	Shipping centers, warehouse
Other	50% commercial floor space	Data center, laboratory
Vacant	More vacant floorspace than used	

For each building type the CBECS provides the sum of major fuel consumptions for a period ranging from 1992 to 2018. The dataset chosen was the 2012 one. Dingel and Neiman in their working paper propose a method to cluster WFH job's data into WFH industry data. It consists in the merging of the derived WFH-SOC dataset (standard occupational classification), obtained from the of O*NET surveys, with the SOC relative 2-digit sector's employment classification from the Bureau of Labor Statistics (BLS) Occupational Employment Statistics (OES) dataset. [74] Once bonded the CBECS and the WFH-SOC-OES datasets together, it was needed a method to compute the share of final energy consumption associated to the WFH "teleworkable" commercial sector. Multiplying the sub sectorial energy consumptions by the WFH shares is wrong, for many reasons:

- A sector's WFH share is not strictly an indicator of how much of the sector related energy can "float" in relation to variations of its value.
- The WFH shares are US and year specific, the same classification performed on a developing country would have returned near zero WFH shares for all the subsectors. In fact the Dingel Neiman national WFH potential could be calculated by first obtaining data for the total number of workers in each industry. Then is obtained the number of workers at WFH by multiplying the number of workers for the indicated Dingel Neiman shares. Dividing the total number of WFH workers with the total number of workers would result in a share similar to the 37% which is the US national WFH level calculated by Dingel Neiman. (To get the exact value should be added to the computation also the remaining noncommercial sectors). Therefore, the multiplication of energy values by WFH values would get a temporal WFH fixed information, not useful for the purpose of this research.
- Of interest was instead the identification of those commercial subsectors "structurally" inadequate to host WFH.

The choice was therefore the identification of an arbitrary cut-off WFH levels that would identify those subsectors likely to be never teleworkable. Their relative energy FC would then be summed and the total divided by total commercial FC. The cut-off

WFH level was set to 14%, equal to the Retail trade one's. Under this method would result not teleworkable "Food Sales and Service", "Lodging" (Hotels), "Mercantile" and "Religious worship". The Health care sector, however, needs considerations.

It was chosen not to include Health sector related energy despite it having a WFH value greater than the cut off one. In fact, most of health care facilities related consumptions are needed to support machineries and a comfortable environment to patients. [75] In other words, the assumption is that energy savings due to some personal (probably high figures who do not perform physical tasks in the hospital) being at WFH are nulls. In table is shown the final binding performed on US, where the last column indicates whether a sub sector is not teleworkable (very low VL) and the overall level of teleworkability (high H, medium M). The so found sub commercial coefficients for US was of 0.53.

Table 3.6. EIA - SOC binding

Energy Information Administration		**Dingel-Neiman (National Bureau of Economic Research)**		**WFH**
Building Activity	Trillion Btu	Industry	Share of jobs from home	Assigned
Education	842	Educational Service	0,83	H
Food sales	262	Accomodation and food service	0,04	VL
Food service	514	Accomodation and food service	0,04	VL
Health care	718	Health care and Social Assistance	0,25	VL*
Lodging	564	Accomodation and food service	0,04	VL
Mercantile	1.008	Retail trade	0,14	VL
Office	1.241	Management,Services,Finance,Information	0,76	H
Public assembly	480	Federal,Local Government	0,41	M
Public order and safety	133	Federal,Local Government	0,41	M
Religious worship	173		0	VL
Service	272	Management,Services,Finance,Information	0,76	H
Warehouse and storage	429	Warehousing,Transportation,Construction	0,19	M
Other	286	Other Services	0,31	M
Vacant	41	Other Services	0,31	M

European Union

For European countries it was consulted the official European Union "EU Building Database", [76] which is publicly available on the European Commission portal. The database can be consulted directly online and most of its data are derived from the "Odyssee" database, which is a project financed by the Commission within "Horizon 2020". 36 European nationals' universities or Efficiency Agency (ENEA for Italy) cooperate in the Odyssee-Mure project. The Building subdivision is similar to the CBECS one, though less detailed. In table are shown the sectors and their relative WFH teleworkability, as was done for the US, subsectors having a VL labeling were not included in the energy summation.

Table 3.7. European Union classification

Sub Sector	WFH
Private Offices	H
Public Buildings	H
Wholesale and trade	VL
Hotels and restaurants	VL
Health care	VL
Education	H

Full datasets reporting energy consumptions for each of the sub commercial sectors were found for Denmark, Germany, Netherland, Sweden and United Kingdom. The results are shown in Figure 3.11 , and show sub commercial coefficients ranging from 0.4 to 0.5, exhibiting almost constant trends throughout the period 2000-2013.

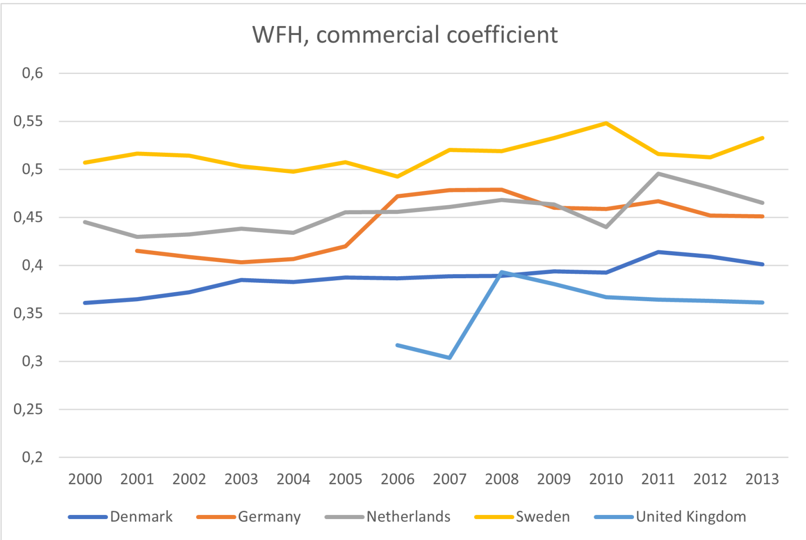


Figure 3.11. sub-commercial WFH coeff. European Union

Australia

Data for Australia were collected from the "Baseline Energy Consumption and Greenhouse Gas emissions, for commercial buildings" reports of 2012. [77] It was released by the Council of Australian Governments and was part of the National Strategy on Energy Efficiency. The report was a study of the Department of Climate Change and Energy Efficiency. Projections made in 2012 were up to 2020 and with a sub commercial level resolution. In the table is reported the commercial Building subdivision and its WFH assigned classification.

Table 3.8. Australia classification

Sub Sector	WFH
Stand Alone Offices	H
Hotels	VL
Retail	VL
Hospitals	VL
Education	H
Public	H
Vocational Education	H

The results show sub commercial coefficients ranging from 0.42 to 0.4, exhibiting almost constant trends throughout the period 2009-2020. However these data were old projections of 2012. Historical trends were therefore retrieved from the Department of Climate Change and Energy Efficiency database. Building mapping was not the same, as in the historical database were both present retail and tertiary subsectors. In Figure 3.12 is shown a combination of historical trends and "future" projections from the 2012 report. They are comparable in magnitude, yet they substantially differ in trends. "History" is slightly increasing, with shares from 40% in 2000 to 44% in 2011. "Future" is instead slightly decreasing, with shares of 43% in 2011 and of 40% in 2020. However, changes are small considered the time range of 20 years.

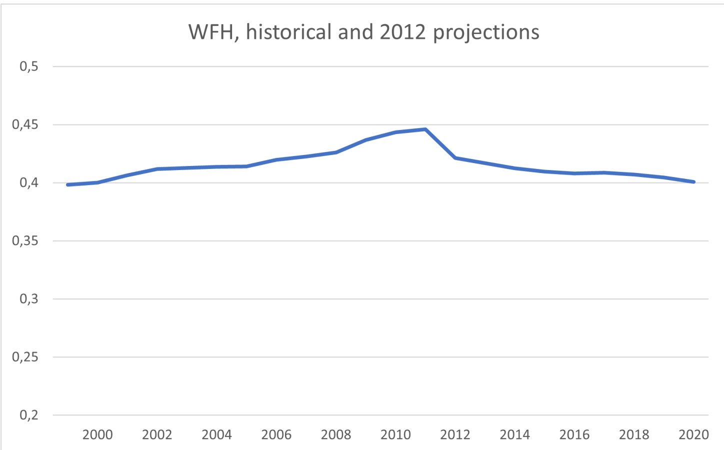


Figure 3.12. sub-commercial WFH coeff. Australia

Singapore, China and India

Data for Singapore were retrieved from the Singapore "Building and Construction Authority" (BCA). [78] BCA published the Building Energy Benchmarking Report

(BEBR) annually since 2014, to monitor the building energy performances of Singapore's building stock. Only publications from 2016/2017 however included also healthcare facilities and civic buildings, sports and recreation centers. The BEBR reports dataset reports Building Type, Floor Area in square meters and the Energy Use intensity in KWh/floor area. Therefore the analysis was limited to electricity consumption. The BEBR dataset is the most detailed one, with a building resolution of 17 use types. In the table is reported the commercial Building subdivision and its WFH assigned classification:

Table 3.9. Singapore classification

Sub Sector	**WFH**
Mixed Development	H
Retail	VL
Office	H
Hotel	VL
Community Hospital	VL
Private Clinic	VL
Polytechnic	H
General Hospital/ Specialist Centre (Public)	VL
Nursing Home	VL
Private School	H
University	H
Specialist Centre (Public)	H
TCM Clinic	VL
ITE	H
Private Hospital (Private)	VL
Private College	H
Polyclinic	VL

Data for 2018 were then aggregated and a resulting WFH subcommercial coefficient of 0.48 was found. Data for China and India are highly unreliable, since they were not collected from an official source while instead from two unique papers reporting a rough estimation of commercial energy consumptions. The index obtained for India [79] was of 0.42 while the one obtained for China, [80] obtained through a reverse energy calculation using carbon emissions as a proxy, was of 0.45.

3.3.3 NAMEA - WIOD Calibration

The trends obtained from method 1 showed a particular constant behavior in recent years, the reliability of data source, excluded India and China, was very high, being all produced by officials governments agency or partnerships. Yet, it was required a greater geographical resolution to apply the commercial sub coefficients to all EDGE regions. The second method adopted consisted in obtaining data from the World Input Output Database (WIOD). [81] An extensive literature on the WIOD can be found at the official website. Yet, a standard Input Output matrix does not contain energy values on FC but only economic transactions from an i-sector to another j-sector. European Commission Joint Research Centre (JRC) released in 2019 a restricted version of the WIOD dataset reporting estimations for embodied energies within cross sectorial transactions, the “National Accounting Matrix with Environmental Accounts” (NAMEA). [21] It was applied to the database a similar classification as performed in method 1. NAMEA dataset adopts the same industry classification of the WIOD, and therefore includes all of national sectors. 19 sectors were labeled as “commercial”, while 14 as teleworkable sub commercial sectors. Classification criteria were the same adopted previously.

For each region in the database was provided a time span ranging from 2000 to 2016. For each year was calculated the subcommercial coefficient and the GDP per capita information (country and year specific) was added. Data were then aggregated by EDGE region. European Unions data were averaged by year to reduce the relative weight of the EU dataset in relation to others world regions. A GAM (General Additive Model) with a smoothing gamma parameter equal 3 was then used to infer a correlation. Results are shown in Figure 3.13

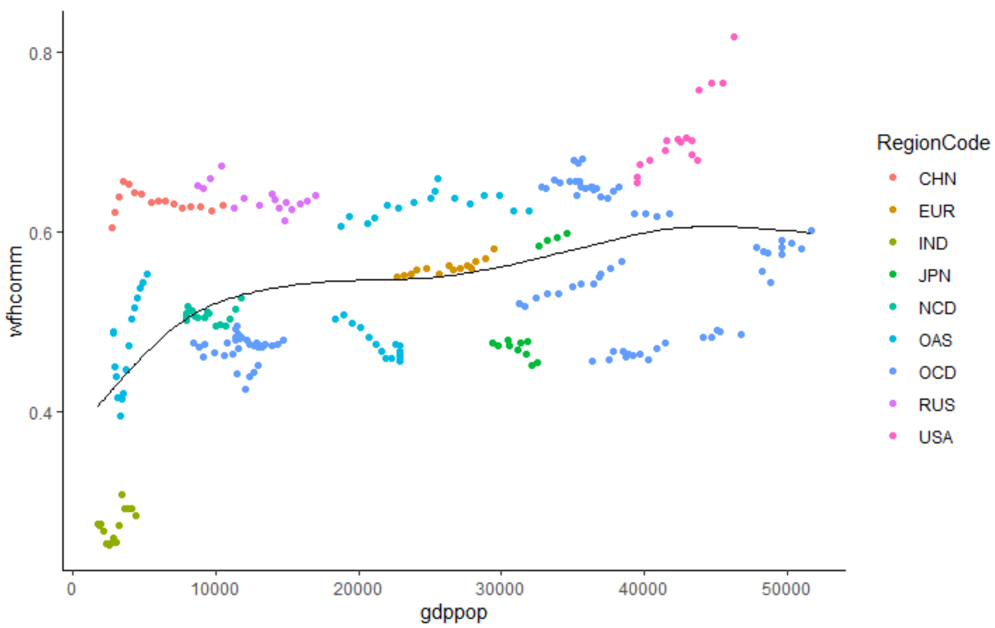


Figure 3.13. NAMEA WFH coeff.

The obtained calibration shows results similar to those obtained with method 1. From values of GDP per capita of 10000 dollars the subcommercial coefficient fluctuate from values of 0.5 to 0.6 independently from the GDP. However a slightly increasing trend can be observed, with the median for higher GDP per capita closing values of 0.6. This could be explained by higher shares of office floor space in more advanced economies. Moreover India results having a coefficient of around 0.3, much lower than the one obtained in method 1 (though unreliable). China instead show high values of around 0.6.

At this point, results obtained with method 1 were on average lower, ranging from values of 0.4 to values of 0.5, while results of method 2 were on average higher, from values of 0.5 to values of 0.6. In the NAMEA related publication is shown a reliability test performed comparing energy results obtained form the modified WIOD database and official energy reports from National Statistical Institutes. According to the authors of the study, a quasi-perfect accordance level should be guaranteed by NAMEA.

Both method 1 and 2 therefore should rely on highly thrustable database, difference in results are thus to be caused by slightly difference SOC and/or industry classifications. In EDGE it was therefore chosen to assign a median value of 0.55 to the subcommercial coefficients, with an adequate variance to be provided in a Monte Carlo simulation.

3.4 Commercial Reductions

Collecting data for Commercial Energy Consumption's variations due to WFH was not an easy task due to the extreme variety in boundary conditions. All found literature was produced amid COVID19 pandemic and reported registered or estimated consumption variations for the entire commercial sector. Two main issues had to be solved:

1. Avoid comparing data collected from countries in very different SIP (shelter in place) regimes.
2. Extract data reporting variations only for the WFH or teleworkable commercial sector as defined in the previous section. Eg. excluding food retails etc.

Then it had to be modeled a function that correlated WFH levels with energy reductions, in this way a spatial and temporal component could be added and thus connected to the EDGE equations. Out of 18 collected data points, 6 relatives to four nations satisfied both condition 1 and 2. Data collected for the others countries were useful to estimate upper boundaries for reductions in commercial consumptions. First is therefore presented an overview of some of registered energy variations during COVID19 pandemic, not satisfying conditions 1 and 2. Then is presented the performed calibration and addition in EDGE.

3.4.1 Collection of Data

Italy was the firs western country to be hit severely by COVID19 pandemic. The implementation of the national lockdown order forced most of Italian population at home (around 40% of the employed population was at WFH [1, 82]) and the closure of "non essential" activities. The order was implemented on 8 March 2020 through a Decree of the President of the Council of Ministers (DPCM). [13] A second order was issued the 22 of March 2020. All commercial and industrial activities were forced to closure for a period extending at first from that day to the 3 of April 2020, and significant effects on the national power grid were registered. [83] Some exceptions were made for the production and industry sector. The energy and food industry were kept open, but most of the commercial sector was limited. Providing a percentage is not possible, the DPCM's list of "exceptions" for the commercial sector is shown in Table 3.10.

The number and entity of exceptions could be misleading. For example, schools and university were closed from the beginning of March, and access to scientific laboratories was very limited. Also, the same DPCM encouraged the adoption as wide as possible of WFH, for all categories, included those in the privileged list.

"Unareti" and "Research on the Energy System) RSE released in June 2020 a report that analyzed energy consumptions variations for the city Milan and Brescia in concomitance with the first lockdowns of March 2020. [84] The analysis consisted

Table 3.10. DPCM exceptions

Commercial sector "exceptions" as of 22 March 2020 DPCM	
Repairing of machines and equipments	Instruction
Energy operators	Social assistance
Water and sewage operators	Postal service
Engineering	Research and development
Wholesale trade (most of) and warehousing	Professional activities
Information	Hotels
Finance	
Call Center (inbound call)	
Public Administration, Defense	

in a review of data coming from the Medium Voltage electric distribution grids. The reference week was the one of 10-16 February 2020 (no SIP). Data for Milan consented only an analysis of overall electricity consumption variations, while those for Brescia allowed for a breaking in sectorial consumptions. In Figure 3.14 is shown the partition of total electricity consumption for the two cities.

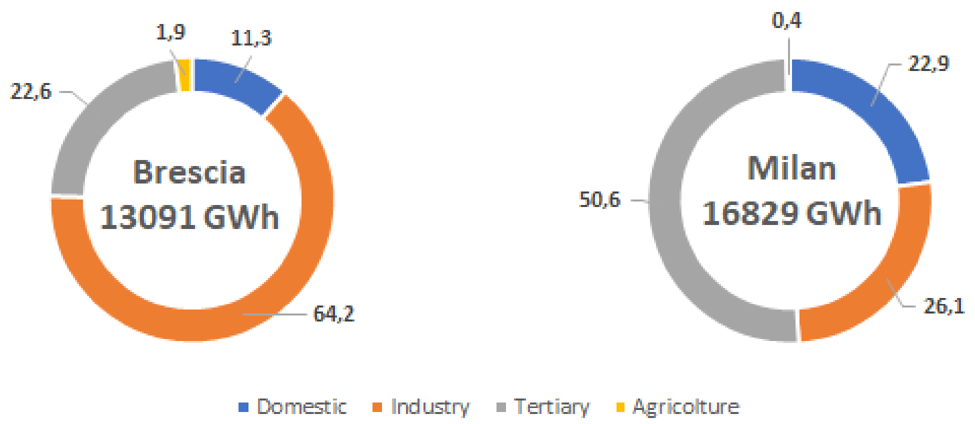


Figure 3.14. Milan and Brescia sectorial bd. GWh/Yr

Brescia has a much higher share of Industry type load, while Milan a much greater Commercial and Domestic load types. In the next figures are shown the variations. The four vertical red lines indicate different levels of SIP orders:

Table 3.11. Lockdown's timeline, Italy

24 February 2020	Closure of all schools and universities
DPCM 3 March 2020	Establishment of first Red Zones
DPCM 8 March 2020	Stay at Home
DPCM 22 March 2020 "Close Italy"	General Lockdown and closure of activities

For the city of Milan was registered a peak coinciding with the 22 of March in electricity reduction equal to -19,4%. Data were corrected for temperature variations.

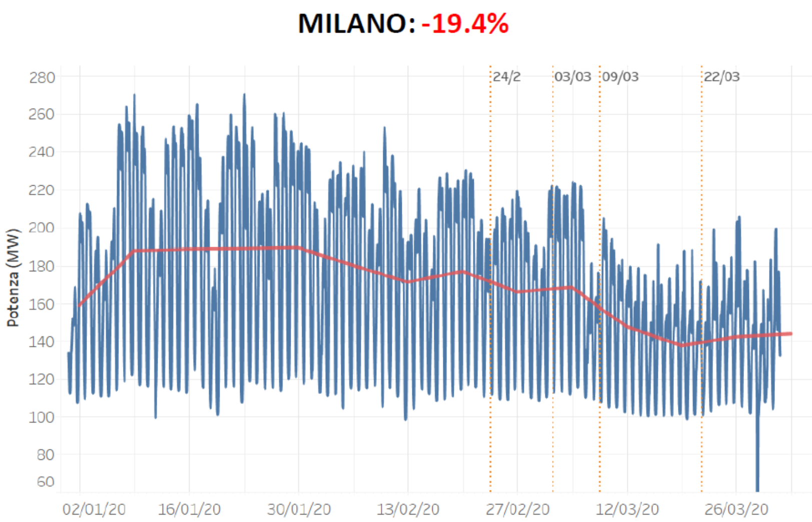


Figure 3.15. Milan electricity reduction, RSE

The 20% reduction in electric consumption is due mostly, according to the report, to a reduction in commercial electricity energy consumption, that accounts for 51% of Milan city. Yet, the real reduction for the commercial sector could be greater, considered the counteracting effect of the residential sector (which accounts for 20% of electricity consumptions).

For Brescia it was possible identifying which Medium Voltage lines were connected to specific types of clients. Thus, variations were disaggregated by sector. At its peak on 22 March 2020, with most activities closed, Brescia commercial sector registered a reduction of 44% of electricity consumption, while Industry experienced a minus 80%. The data obtained from this report were not used in the EDGE calibration since no information were provided for the various commercial sub sectors.

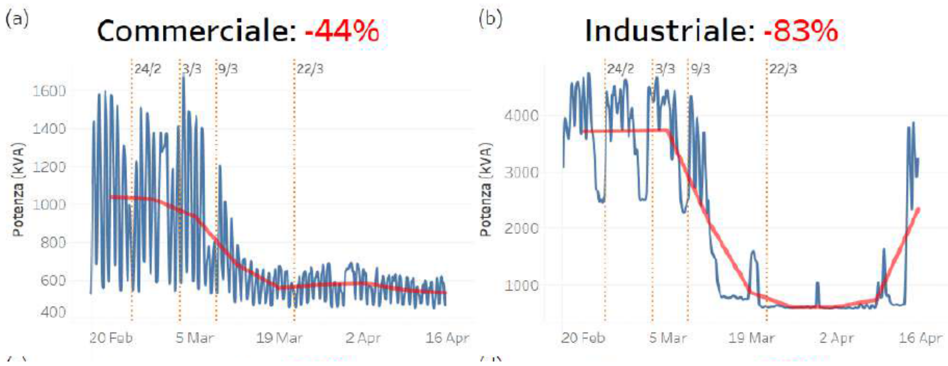


Figure 3.16. Brescia, Commercial and Industrial reduction, RSE

3.4.2 Nature Climate Change

Estimations for the reductions of commercial energy consumption in the world, due to COVID19 related lockdowns, were performed by Le Quéré C. et al (Temporary reduction in daily global CO2 emissions during the COVID-19 forced confinement, Nature Climate Change July 2020) [4, 85] and by M. Forster P. et al. (Current and future global climate impacts resulting from COVID-19, Nature Climate Change October 2020). [11]

Le Quéré et al. method to estimate commercial variations is based on surface transport data for the upper limit, with the assumption of it being proportional to the change in the workforce, and on electricity changes for the lower limit. A central value is then interpolated. In such a way the study correlates three confinement levels to changes in "activity" and calculates a maximum decrease in sector world emissions of 21% (-8 to -33) for the 7 of April 2020. Level 2 of confinement already impacts extensively on the commercial sector, and in particular on WFH related sub sectors (offices, schools, public buildings).

Table 3.12. SIP levels

Level	**Policy example – commercial related**
1	None
2	Closure of schools, universities, public buildings, religious or cultural buildings, restaurants, bars and other non-essential businesses.
3	Confinement for all but key workers

Table 3.13. SIP's activity variations

	Level 1	**Level 2**	**Level 3**
Public and Commercial, activity variations	-5 (0 to -10)	-22,5 (0 to -40)	-32,5 (-15 to -50)

The second study performed by M. Forster P. et al. take advantages of the enormous amount of mobility data collected from the Google and Apple mobility database. Data are relatives to 114 countries and tracks movements of 4 billion users. The sector approach adopted is the same of Le Quéré et al. but substitute the percentage changes in the emissions with Google mobility changes in transit. The authors report that the estimates produced with the Google transit method are likely to overestimate the emission change from the sector. Results should thus agree more with the high estimates from Le Quéré. In table are shown the projections made by M. Forster, where "peak" stands for the peak of a probability distribution (not the mean). Results are overall similar to the one found for Brescia (-44%).

Table 3.14. M.Forster et al. CO2 reductions

	Le Quéré et al.	**M. Forster et al.**
Peak %	-50	-45
Max %	-50	-80
Min %	-30	-20

3.4.3 Other Data

A review of source of data estimating energy or emissions variations for the commercial sector during lockdowns are shown in the table below. Those used for the EDGE calibration are reported in the next paragraph.

Table 3.15. Other commercial data

Ref	Description	Country	Delta
[86]	HIS market research	China	-3,1% elec.
[87]	EIA	US	-8% elec.
[84, 88]	Unareti – RSE	Italy -Brescia	-44% elec.
[4]	Le Quéré et al.	World	-50% emissions
[11]	P. M.Forster et al.	World	-21% emissions
[89]	Stark Energy Provider	UK	-29% elec.
[90]	Food, Retail Sales and Services	ARG	-16% elec.
[91]	Energy Network Australia	AU	-7% * soft lockdown
		BR	-26%
		MX	-39%
	OLADE	Central Am	-16%
[92]	Latin America Energy Organization	Zona Andina	-24%
	”Energy consumption” Mtep	Cono Sur	-21%
		El Caribe	-26%
		Latin Am	-25%

3.4.4 Calibration

Italy

In order to grasp the dynamics involved in an office during lockdown and its energy impacts, it was chosen to monitor a building in Verona (Italy). The building host an ITC company involved in the provision of management software and business development assistance. It has good overall energy performances and was certified with a more than sufficient “sustainability rating” by the Italian private company “SI Rating” (Sustainability Impact Rating). The ITC agency had also been experimenting WFH or greater levels of work flexibility in the last years. WFH was never adopted systematically, and only for some days a week. However this past “training” facilitated a fast and efficient adoption once it became mandatory the 22 of March 2020. In fact the agency had already placed more than half of its 80 workers in WFH from the beginning of March. A level of 70%-80% of personal at WFH was reached at its peak in late March, some personal was still coming at office because the agency was included in the list of those “exceptions” listed by the DPCM of 22 March 2020.

Energy consumption were of about 80 MWh a year in the last four years, [93] with no increasing nor decreasing trends signaled. Usual profiles of consumption show increases of about 14% in concomitance with the hotter months of the year. The relatively modest increase in summer proof that cooling energy demand does not play a significant role on overall consumptions. Hence variations registered during the first lockdown of March-April 2020 are potentially valid for the rest of the year. Results indicate average reductions of about 27% of total electricity consumption in concomitance with WFH levels of 70-80%. This result is discussed later.

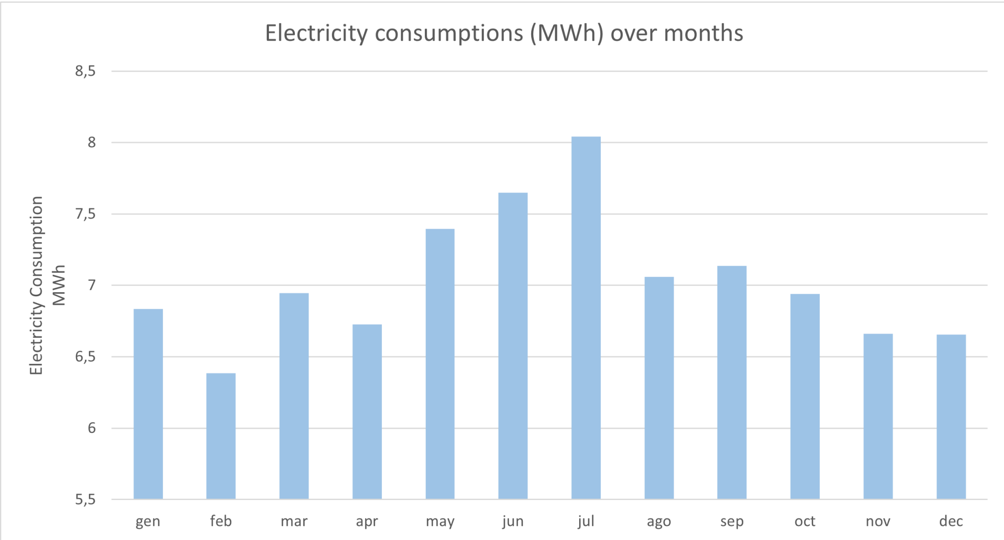


Figure 3.17. Office consumption profiles

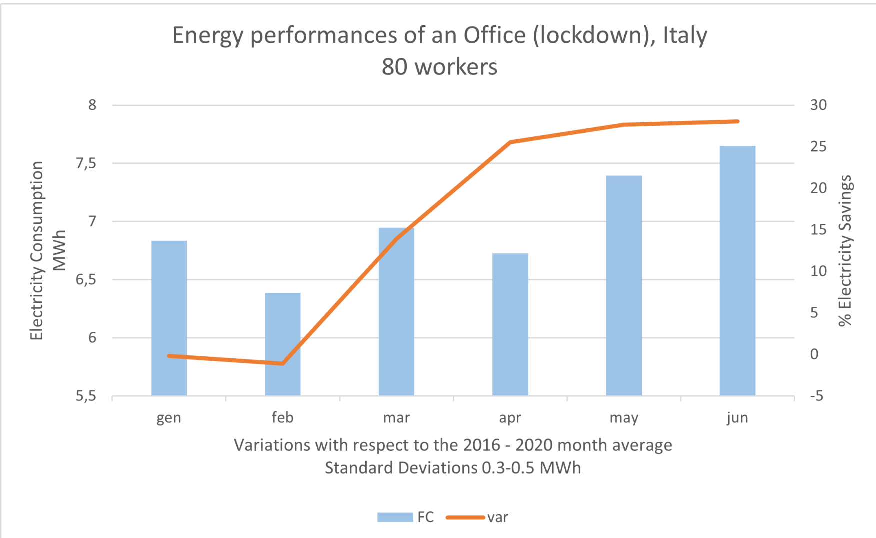


Figure 3.18. Electricity variations with COVID19-WFH

Sweden

Zhang X, Pellegrino F. SHen J and others from the Department of Energy and Community Buildings of Dalarna University, in Sweden have investigated in a pilot study the impact of confinement measures due to COVID19 on energy demand of a building mix in a district (non-existing virtual community). [16] This work turned out to be of great use for the purpose of this research, as it offered insights also on the dynamics involved in the residential sector. To simulate the energy performances of the district was used "Urban Modeling Interface" (UMI) a free modelling tool developed by the MIT Sustainable Design Lab. One of the key parameter modified to account for energy variations was the occupancy profile, that due to the different confinement levels, differed from the conventional one. To exemplify the level of thermal details implemented in this model, must be mentioned the fact that offices and school show lower thermal gain with increasing level of unoccupancy. The different types of commercial buildings modeled are school, offices and retail shops, the first two being of interest for this WFH research.

In a similar way to the method adopted by Le Quéré et al. three different levels of confinement are modeled, the most important scenario property being the unoccupancy hours, is reported in the table below:

Table 3.16. Zhang et al. classification

Closures ratio	Office Building	WFH equivalent
Level 1 base case no COVI19	15hr - 9hr of work	0
Level 2	19.5hr - 4.5hr of work	0.5
Level 3	21.75hr – 2.25hr of work	0.75
Level 4	Full closure	1

For office building type (8.1% of total district area) the following results are provided in the study, with total energy expressed in KWh/m^2 but being equal to the sum of Lighting, Equipment, DHW, Heating and Cooling energy demand:

Table 3.17. Zhang et al. FC variations, tot

Closures ratio	WFH	Total Energy demand	Variation
Level 1 base case	0	72.1	0
Level 2	0.5	60.6	-16%
Level 3	0.75	58.9	-18%
Level 4	1	53.7	-25%

For electricity demand the pattern is the following:

Table 3.18. Zhang et al. FC variations, EL

Closures ratio	**WFH**	**Delivered Electricity**	**Variation**
Level 1 base case	0	48.5 (70% total)	0
Level 2	0.5	29.9	-38%
Level 3	0.75	26.7	-44%
Level 4	1	17	-65%

While for the system energy demand, equal to the sum of DHW, Heating and Cooling:

Table 3.19. Zhang et al. FC variations, Heat and Cooling

Closures ratio	**WFH**	**Total Energy demand**	**Variation**
Level 1 base case	0	23.6 (30% total)	0
Level 2	0.5	30.7	+30%
Level 3	0.75	32.2	+36%
Level 4	1	36.7	+55%

From the results its clear the strong reduction in appliances and equipment energy demand due to their progressive unuse. Levels of reduction reach -65% in a case of full office closure. However this demand reduction is counterbalanced by a decrease in thermal gain due to the less occupancy and equipment switched off. Total energy reductions were used as three points of calibration, for the three respective levels of WFH. It was chosen not to consider separately electricity and system energy demand to avoid being too specific and risking of giving too much weight to environment or climatic local parameters.

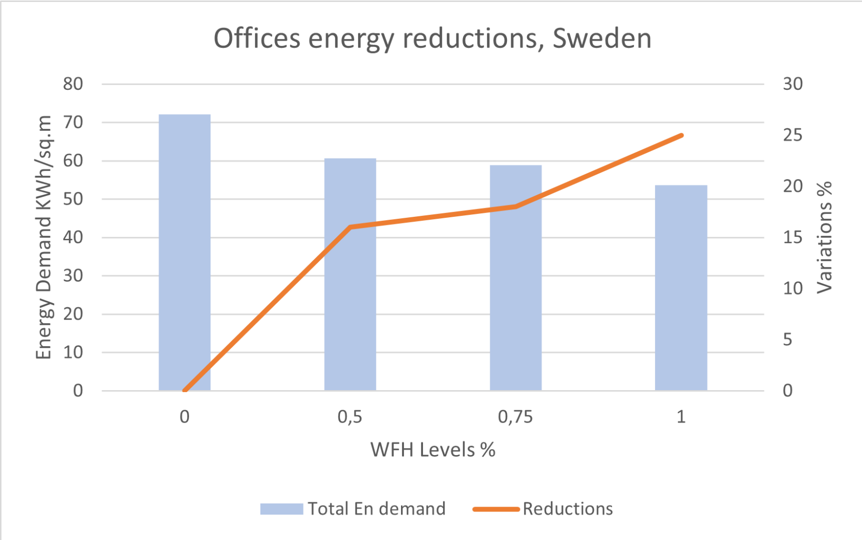


Figure 3.19. Sweden,(district) office energy reductions

UK and US

Data for United States and United Kingdom were retrieved from two energy providers and research utilities, respectively "Hatch Data" [18] and "Carbon Intelligence". [15] Hatch Data supports building operations teams and owners in managing energy performances and in identifying potential building quality improvements. Their platform captures building data for more than 400 million square foot of occupied space. They report having a database containing 14 billion hours of property operating data collected over 10 years. In order to identify energy reductions due to forced closure of US commercial office space it was performed an aggregation of minute-by-minute data received from utility meters and other building equipment. Their report "How is U.S Office Building Energy Use Being Affected by the Coronavirus Crisis?" compare the last three weeks of March 2020 and the first of April with the weeks prior to March 1 and therefor to the public health crisis. On a national basis they found office building electricity consumption declined of 22% in the weeks analyzed, with the reductions being correlated with the timing of setting of SIP orders, which began effective in US from the 19-24 March 2020.

Data for UK were retrieved from Carbon Intelligence, an energy performance consultants. In a report released in August 2020 the founder of the agency reports: "Unfortunately the vast majority of buildings are not well managed and that has become really obvious during the lockdown. The average building, despite being empty, is still using over 80% of the energy it consumes when it is full, and that is mad". In fact across a sample of 300 offices and hotels, the average energy consumption dropped of only 16% in the last week of March, when the government had ordered work from home, social distance and banned travels. Despite these measures the worst 10% of buildings still used around 97% of their typical energy demand. The assignment of WFH levels for the US and UK data points was based on assumptions

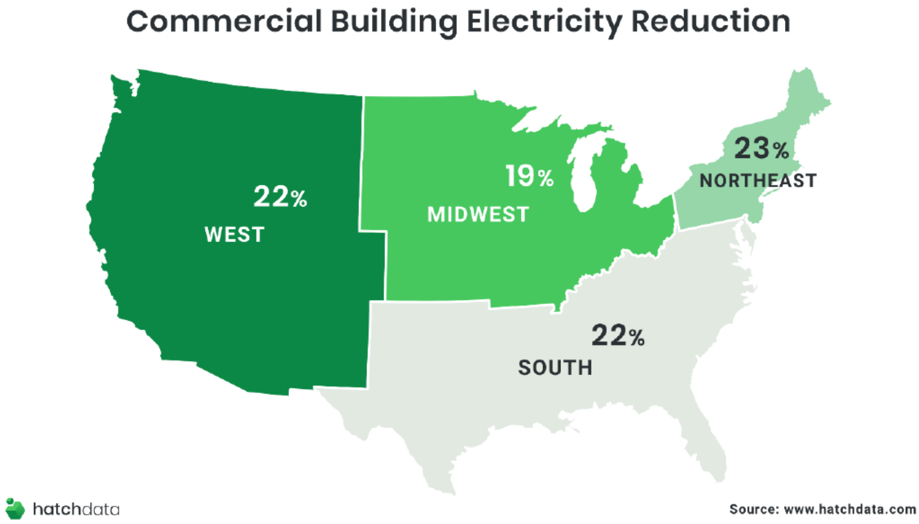


Figure 3.20. US, office energy reductions

on national SIP orders, which were at this point of time (second half of March 2020) similar to those registered in Italy. It was therefore decided to assign a conservative value of 65% of WFH.

Office energy consumption

"It was a bit surprising, looking at the data, that these reductions were not larger"

(Hatch Data report, August 2020)

The collection of data points for UK, US, Sweden and Italy allowed the calibration of an "WFH commercial subsectors energy reduction curves". Datapoints for Sweden as mentioned before refer to total energy consumption, however due to the simulation nature of that study and to some peculiarities involved, (like different levels of WFH) it was decided to include them in the calibration. The so obtained calibration show a linear increasing trend in "energy" reductions with respect to WFH levels. In EDGE it was decided to simulate such energy reduction as a total one, approximation allowed by the nature of commercial energy carrier mix, which is mostly composed by electricity, all over the world.

The reasons for a so humble reduce in consumption despite high levels of WFH is to be found by a breakdown of commercial final consumption per end use. An estimation performed by the EIA on 2007 data show that only a minor part is due to consumptions by the personal. Computers and office equipment, account for about 20% of total commercial energy consumption. The vast majority of consumptions is related to space heating, cooling ventilation, lighting, which are often centralized etc. In particular Heating, Ventilation, and Air Conditioning (HVAC) systems account at least for a third of building consumption. The mechanics and substances used for

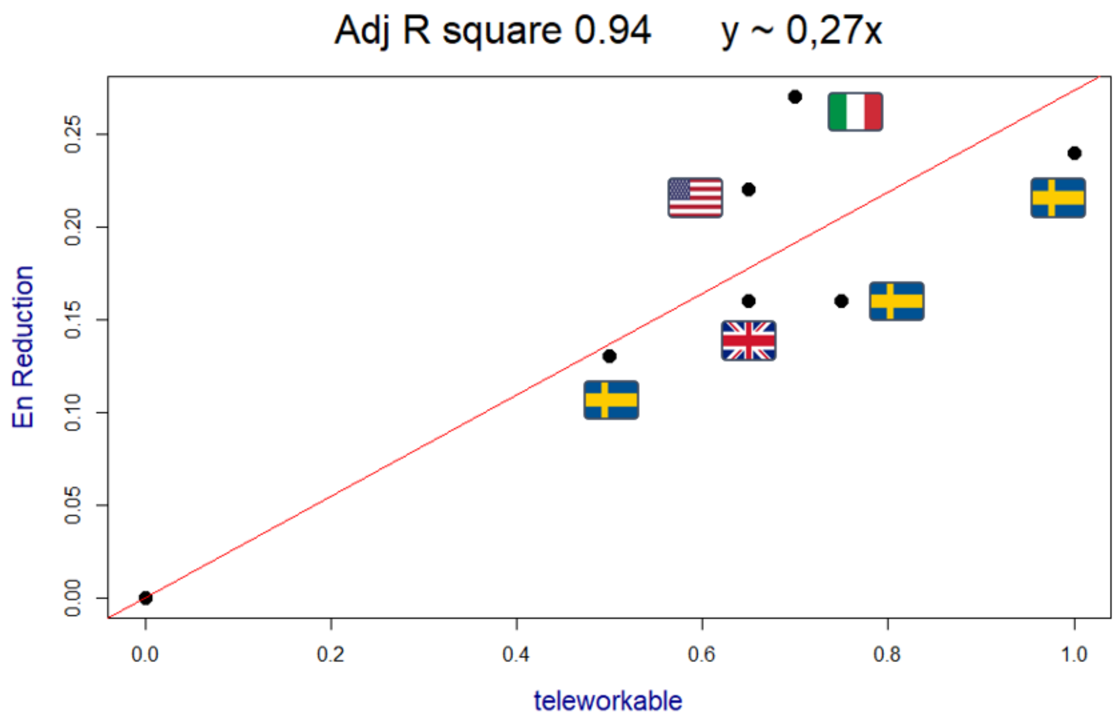
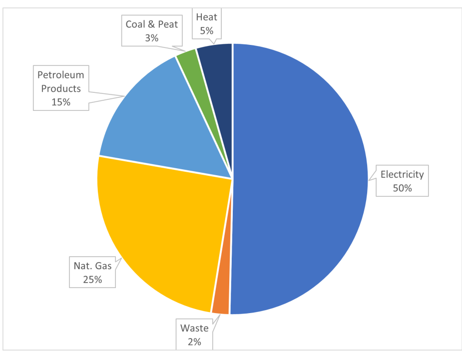
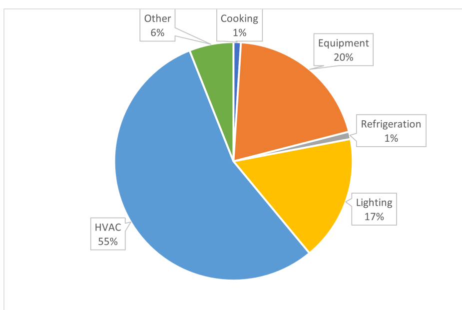


Figure 3.21. WFH sub sector, calibration curve



(a) Commercial sector energy use, IEA 2007



(b) Office End Use bd. US DOE 2008

Figure 3.22. Commercial sector

their operation need to be always active to avoid damaging the systems. For example, uncirculated water could lead to corrosion phenomena. [15, 18, 94] Elevators shut off for long periods require a technical supervision for their new activation, emergency lights must be always active to comply with regulations, security systems can never be switched off. Moreover some companies may have servers or data processing and storing units inside buildings, and their functioning must be guaranteed to allow workers operating at WFH. Lighting is most of the cases centralized, which means that zoning is not at place. Therefore even if 20 or 30% of the personal is inside the building, all lights will likely be on. Furthermore, as Hatch Data reports, in the rush out of the office as lockdowns were put in place, millions of coffee machines, water coolers, computers and other appliances were left plugged in, resulting in a significant cumulative stand-by power. “Commercial buildings are way more complex than home. Unless you are totally mothballing a building, it’s very hard to switch off everything”, reports Carbon Intelligence.

Yet there is a wide margin for improvements, considered that the commercial sector, and in particular the WFH one (as defined in this research) had never experienced such high levels of unoccupancy before. Both Carbon Intelligence and Hatch Data report that the building industry should develop a sort of stand-by mode for buildings. A “single button” that can reduce energy consumption down to a minimum, for different levels of occupancy, like 50% or zero. Carbon Intelligence sets as an efficiency optimal performance, reductions in the region of 50% for levels of unoccupancy (WFH) around 100%, and provides examples of improvements that could be related to low-energy water circulating HVAC mode, elevator hibernating settings and emergency and security lights that can turn off when there is no personal at office.

Equations in EDGE

In light of the previous consideration it was decided to model in EDGE two curves relating energy savings and WFH potential levels, calculated with the Dingel Neiman or DN and World Bank methods. A first curve was the linear one interpolated during COVID19 lockdowns, assumed to be the worst case scenario, where systems and HVAC are not adapted to the new buildings operating conditions. A second curve represents instead a sort of best case scenario, a future where a “stand-by building mode” is developed and savings for about 60% are reached for levels of WFH equal to 50%. The choice of the curve was for a logistic one, that allowed to add a “learning” and temporal dimension to the phenomena. In fact as GDP per capita of a country increases, also WFH potential increases. First buildings are following the “COVID19” calibration curve, than as the economy grows, more attention is given to energy saving performances and stronger improvements are implemented. For higher levels of GDP per capita a saturation efficiency level is reached and marginal improvements are lower. The delta between the logistic curve and the COVID19 curve was equally discretized (with N equal 50 being the same for all levels of WFH) and 50 possible curves were implemented in the model. The set up was then implemented in a Monte Carlo method that assigned a different efficiency curve at a world level according to a probability distribution. The equations implemented are the following, where the first one is calibration curve, the second the logistic curve and the third the discretized curves implemented in EDGE. In the third equation α equal 0 returns the COVID19 curve while α equal 50 returns the logistic curve.

$$coefCM = 0.27 \cdot WFH \tag{3.6}$$

$$coefCM = \frac{1}{1 + e^{-0.12(x-0.5)}} \tag{3.7}$$

$$coefCM = 0.27 \cdot WFH + \alpha \cdot (\frac{1}{1 + e^{-0.12(x-0.5)}} - 0.27 \cdot WFH)/N \tag{3.8}$$

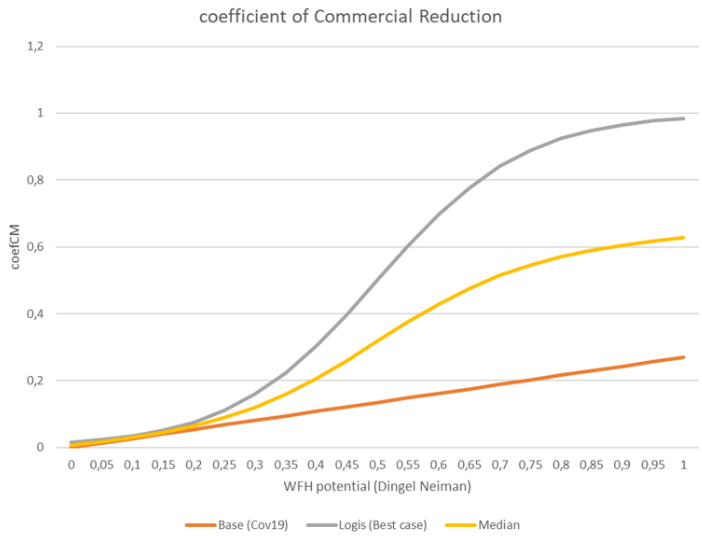


Figure 3.23. Coefficient of sub comm. (WFH) reduction

3.5 Residential Increases

The most demanding part of this research was the definition of a coherent method to estimate the increases in residential consumption due to increased occupancy levels, as consequence of higher WFH levels. In particular the most challenging issue was discriminating among the different sets of data collected during COVID19 lockdowns which where more likely to contain WFH related information. The issues to be solved were:

1. Most data refer to all-clients, averaged increase in consumption.
2. Lack of information about weather and seasonality.
3. Extremely scarce literature.

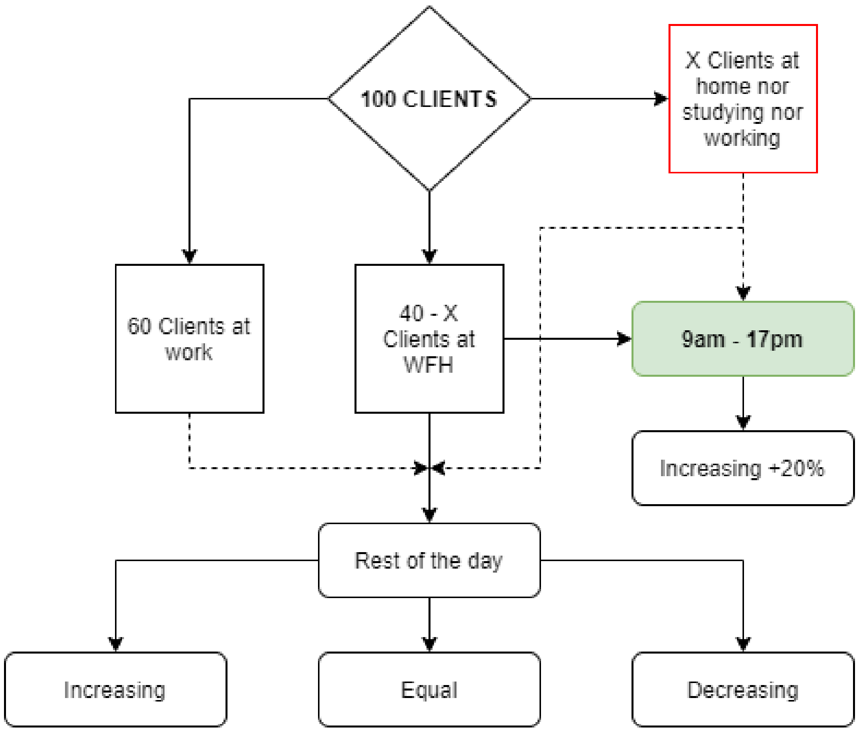


Figure 3.24. Residential, main issues

The first issue requires a brief explanation and is showed in a scheme. A full characterization of the phenomena would have required a much longer and statistically accurate analysis of data and in particular the retrieving of official data reporting employment rates, local cultural preferences (eg use of TV), indications about the number of family members, the floor space per capita etc. These analyses were nor possible nor needed, at such level of details, since the purpose of this pilot research was to provide a first quantification of the impact of WFH at a world level. Nonetheless, the series of assumptions made is here presented:

- Working hours are assumed to be from 9am to 17pm.
- As a reminder, students and in general the Education comm. sub sector is considered a WFH sub sector.
- It is assumed that the types of customers analyzed are two, a first group at WFH and a second at work. Those staying at home during lockdowns but not working are not considered.
- The increments registered during working hours are consequences of WFH activities (equipment, more cooking etc.) and are not related to behavioral shifts. (eg. starting doing laundry during the day instead that at evening)
- Change in behaviors and energy uses before or after working hours could be relevant but were not analyzed due to the possible bias brought by the group of clients returning from home but forced to stay at home due to lockdown measures. For instance, it could be that a client at WFH after being all the day at home adopts different behavior the evening and reduces his/her energy consumption in that time window by watching less TV or going to sleep at different hours. [5, 95–97] In this case energy consumptions variation from 9am to 17pm would not be fully representative of his/her energy variations.

These issues could have been managed better if instead of a top down statistical approach, it was chosen a bottom up approach, that went through the characterization of profiles of consumptions, differentiating by type of appliance etc. However the weak side of such approach would be the relying on cultural and behavior specific consumption pattern, provided that a full world-region analysis is not performed. It was therefore chosen to adopt an easy scalable and less specific statistical approach by trying to estimate the incremental consumption in electricity use of a smart worker. As is shown in the diagram, the analysis was therefore limited to working hours, including in such a way possible clients staying at home (due to lockdown) but not working. Yet the effect of this group on the results was assumed to be not influent.

The method adopted consisted in obtaining rough estimates of the increase in residential consumption sources of energy, namely Electricity and Gas. These data would provide the subsequent found data about End Use variations of higher degree of reliability. In fact the two types of variations were cross checked through their application into an End Use (EU)-Energy Carrier (EC) matrix. For the EC variations statistical approach were used, with the method aforementioned. A first block of data was obtained from an external source, Octopus Energy, which was cited by most of 2020 literature regarding COVID19 lockdown energy implications. A second one was obtained through personal analysis of a smaller dataset, performed with the same method implemented by Octopus. For the EU variations instead, it was not possible to define a method for the separation of the cohorts of WFH and normal workers. However the legitimacy of these data was provided by the EC-EU method.

3.5.1 Energy Carrier

Here is provided the set of data collected for Electricity and Gas consumption variations but not exploited in the calibration. The reason for their non-utilization is to be found in the absence of WFH separation or in the presence of strong local peculiarities potentially affecting (greatly) the results. Some of these data are explained in the next paragraphers.

Table 3.20. EC variations in residential sector

Ref	Description	Country	Increment
[98]	Sperimental S4 EnergyPlus simulation	Serbia	+55% S4
[99]	352 “representative customers”	China	+40% * lighting
[100]	300 apartments	US, New York	+23%
[101]	Energy provider utility	Singapore	+16%
[16]	Sperimental simulation for a building mix at a district	Sweden	+18% S2
[102]	113 Homes, 3 years data collection	US, Texas	+20%
[103]	700’000 Homes	US	+25%
[104]	80 Homes	India	+26%
[105]	India	India	+13%

Electricity

Studies with few houses sampled: India, a +26% in use of electricity was registered during the first lockdown period, but the sampled homes were only 80. [104] Others studies made in the US, Texas, [102]revealed a +20% in electricity consumption. Yet, the samples houses were only 113, plus half of them had EV with possible consequences on consumption behavior (eg. possible different cost of electricity and higher propension to consumptions). Data from New York evidence an increase in consumption of 23%, yet only 300 apartments were sampled. [100]

Study with higher sampled house but no WFH indications: Another study from India revealed an increase at national level of 13%. [105] A very good data source from US was provided by “Uplight”, [103] whose data team collected readings from two different US geographies, using over seven billion hourly Advanced Metering Infrastructure (AMI) , commonly known as smart meters, data points for more than 700’000 homes. They confronted data for the first four weeks of US lockdown with the previous year data point and corrected these data for temperature, weather, daylight savings times and weekend versus weekday use. The study found out that residential usage was up more than 20% in one region a 30% in another, with respect to normal levels. The company projected these trends to hold in the hotter months of the year, due to higher levels of electricity utilization needed for cooler.

Also the same study presented before in the commercial sector, focused on simulating a district in Sweden, provided results for the increase in residential consumption.

However only data regarding electricity consumption were collected as heat demand was biased by the presence of a district heating systems that caused zero variations on the heat demand. The increment found was thus of 18% for electricity at a level 3 of confinement. [16]

Lastly, Singapore energy provider registered a national 16% increment in electricity consumption. [101]

Study that could offer insights on WFH: A study was performed by Cvetkovic D. et al. from the University of Kragujevac, Serbia and published in October 2020 on “Energy and Buildings” [98] that tried to simulate with EnergyPlus the effect of lockdowns on a household located in Kragujevac. This study “Impact of people’s behavior on the energy sustainability of the residential sector in emergency situations caused by COVID19” thus had the potential for being included in the calibration in EDGE, however the strong local nature of assumptions and the fact that the simulation involved only one household did not allow for it. In the study, in an approach similar to the Swedish one, four different levels of confinement were defined. A reference case S1, a mild protection scenario S2, a semi-quarantine scenario S3 and a complete lockdown S4. The time resolution implemented in EnergyPlus was of one minute and occupant’s age, occupation, lifestyle, habits and lockdown measures were taken into account. Habits were chosen in accordance with cultural and socio-economic local environment. According to the study, the increase in electricity consumption could increase of 58% in the case of a full lockdown. The S4 scenario involves a total ban of movements and only one person is allowed to leave the house once a week for a period of 2 hours to go to the store. The results are shown in the picture below, where is evident the S4 58% increment in electricity consumption. The result differentiates from the others found as it refers to a WFH scenario, while the others were national averages. Yet the reliability of this data point is unclear, for example, the increase in electricity consumption does not change between scenario. Some local dynamics may be involved.

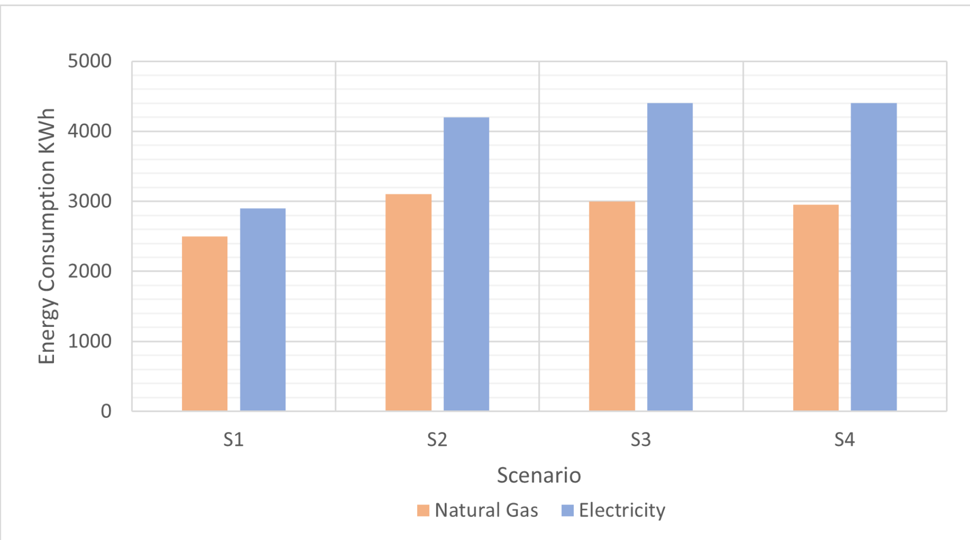


Figure 3.25. Residential increases in an household, Serbia

Gas

The collection of data for gas consumption was more difficult, probably because gas smart meters are not in use as the electricity ones. The same study performed on a Serbian household returned increments in gas consumption due to lockdowns equal to 21%, with little variations across the scenarios. Singapore energy provider reported increments of 34%, while "Tado", a provider of smart thermostat, announced on its online platform a review of readings streaming from 100'000 Tado homes. According to Tado, UK experienced a 15% increase in "heating consumption", while Italy and Spain of 41%. Tado did not provide any insight on what they meant with "heating consumption". These datapoints were thus not taken into account.

Table 3.21. Gas variations in residential sector

Ref	Description	Country	Increment
[98]	Sperimental S4 EnergyPlus simulation	Serbia	+21%
[99]	352 "representative customers"	China	+60% cooling heating * number of hours/d
[101]	Energy provider utility	Singapore	+34%
[106]	Tado® smart thermostat.	UK	+15% * "heating consumption"
	Sample of 100'000 Tado® homes.	IT - SPAIN	+41% * not confirmed by SNAM raw data

Gas and Electricity

An average of the collected datapoints for electricity and gas is shown, with the relatives standard deviations. An average increase of 22% was registered for electricity, while the one for gas was of around 20%. These data are not the one implemented in EDGE. As is shown in the next paragraph though, results obtained through a more rigorous method that tried to separate WFH and normal workers cohorts did not diverge from these data. This could suggest that real increments per home workers are higher than those obtained through statistical methods implemented by Octopus and in this research.

In fact, average increments cannot mathematically be higher than the WFH group restricted ones. The reason why they do not diverge is also to be found in the fact that around 40% of the population was at WFH, and the rest of the population not at WFH also likely increased its consumption.

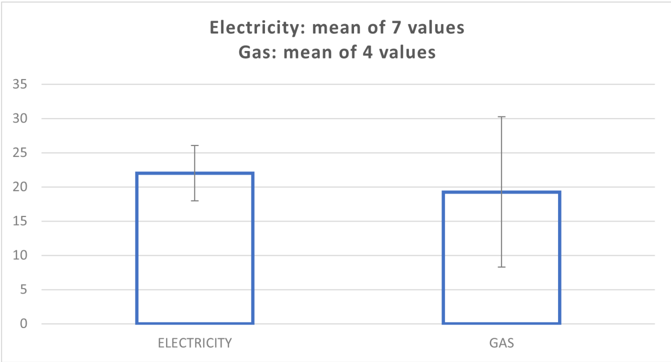


Figure 3.26. Average EC Residential increases

3.5.2 EC, Octopus Energy

"Octopus Energy", a British energy provider, tried to measure the impact of COVID19 lockdown to its client, and in particular developed a method to analyze readings from smart meters and infer the share of clients at WFH and the extra energy that they consumed. The report [12] published in its website was highly cited in literature throughout all 2020, and its results served as input data for the two Nature Climate Change articles mentioned before in this thesis. Moreover, IEA updated "Work From Home" energy scenario included Octopus data points as calibration parameter.

Octopus collected data from 115000 clients both for Electricity and Gas consumptions. The week starting on 16 of March saw in UK a rapid escalation in measures designed to halt the spread of Covid 19. On Monday 16th, the government ordered to avoid social contact as far as possible, favored the adoption of WFH to work from home and prohibited the access to pubs, clubs, restaurants and theatres. Octopus compared usage data from the first week of lockdown with the week before and identified in increase in daytime energy usage that they attributed to more customers being home during the day. They developed two methods to try to infer the incremental energy per home worker. A first method "consistent increasers method" consisted in defining a rule to profile a WFH worker. Only clients showing increments from 9am to 5pm for all four working days were defined at WFH. A second method instead, "mixture method" which is the one replicated by this research, consisted in analyzing statistically the binned load profiles and inferring energy variations. The results (weather and seasonality corrected) that Octopus obtained from these methods are shown below:

Table 3.22. Octopus methods

	Method	WFH	KWh per day	Incremental usage
Electricity	Increasers	17	3.2	32
	Mixture	30	1.5	13
Gas	Increasers	8	9.4	20
	Mixture	25	11	20

A first consideration can be made. The share of WFH found with all methods is far below the estimated one for UK for that period of time, which was around 40%. This difference could be due to the fact that the pool of analyzed Octopus Clients, despite being reportedly representative of UK domestic users, show consumption trends higher than the average, characteristic of an "high usage users" group. The great difference between incremental usages obtained with the two methods signal the noticeable amount of uncertainty surrounding these estimates. Also, an incremental usage of 13% seems to be very unlikely, as also Octopus reports, being lower than the mean increment of 20% presented in the previous paragrapher, which refers to the average of all clients increased consumption. It would require that WFH and normal clients increment in the non working hours offset by a lot the increments during working hours, or that only the cohort of non WFH workers increment by a lot consumptions in the evening while the WFH cohort does not. But neither the first nor the second hypothesis are supported by data, as also the same Octopus load plot demonstrates:

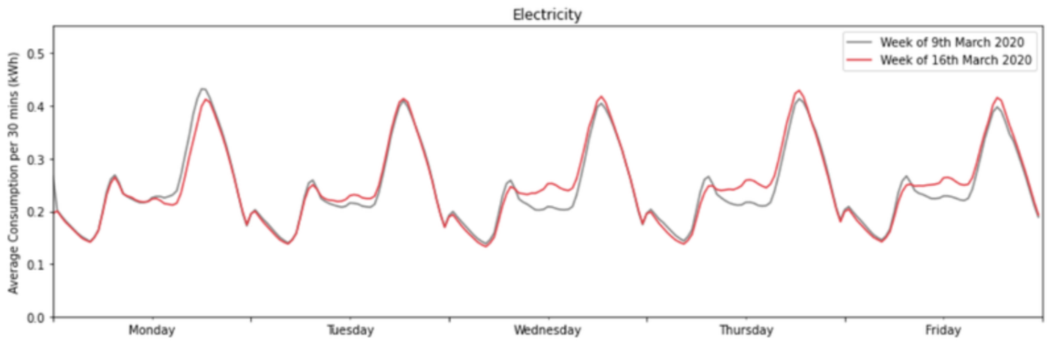


Figure 3.27. Load curves, Octopus

It is thus more likely for the real increment in electricity consumption per home workers being closer to the 30% value.

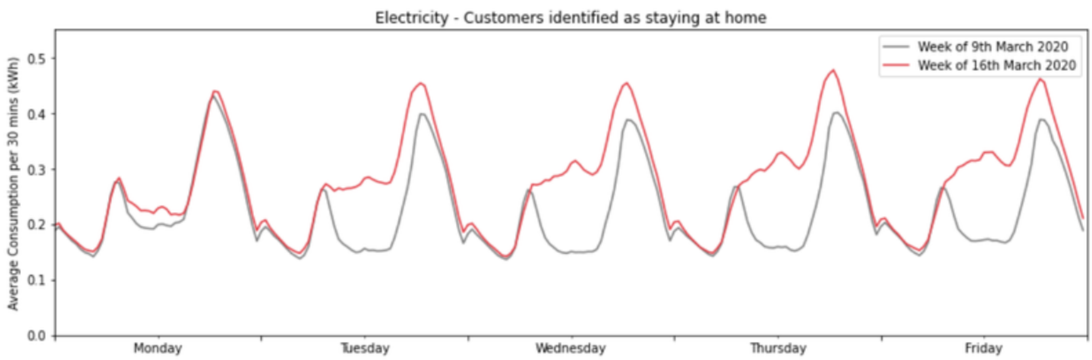


Figure 3.28. Consistent increasers, Octopus

3.5.3 EC, Italian multi-utility

Data were collected from 1215 unique clients residing in the geographic areas of North-Central Italy for the week 24-28 of February (week 1) and the one of 16-20 March (week 2). The national full lockdown was in place from the 22 of March however most of commercial activities were already closed as well as schools and universities from the 11 of March. Average temperatures in week 1 and week 2 differed of about 1°C and therefore weather did not influence the results.

In figure are shown the load curves for the week 1 (black) and for week 2 (red). The order of plotting is Sunday-Saturday, with the five central load curves representing work days. Overall energy consumption increased of 5.8%. In a second picture are instead shown the average consumption variations for each day hour from (from 0 to 24). The black line shows the average of all week days, and each point represents an electricity consumption variation for that combination of day-hour. It was calculated by aggregating together all customers consumptions by day-hour in the week 2 and in the week 1. It shows average increments in working hours consumption from 15 to 20%, with decreases in the morning time. This trend was also observed by Octopus and signaled a behavioral shifts of workers and occupants, that started to wake up and work later due to the avoided commuting time.

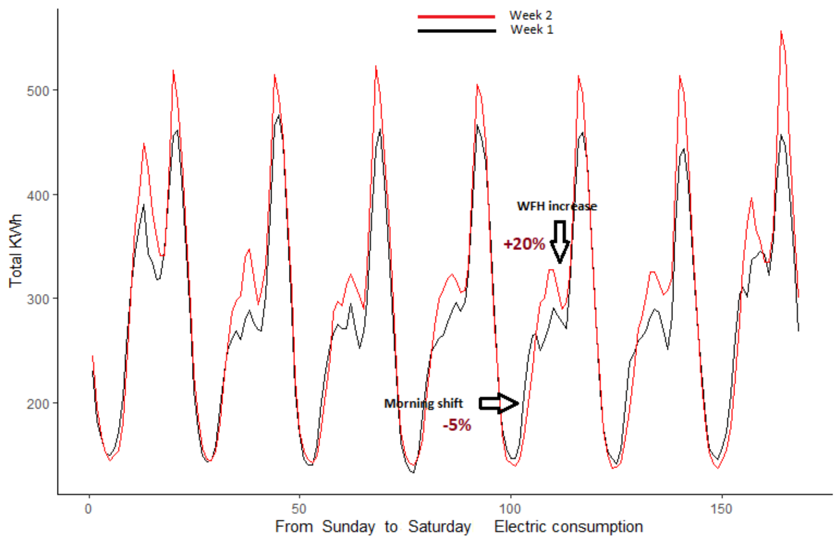


Figure 3.29. Load curves, obtained from metering infrastracture (AMI)

It was then applied the “mixture method” from Octopus, that consisted in the following phases:

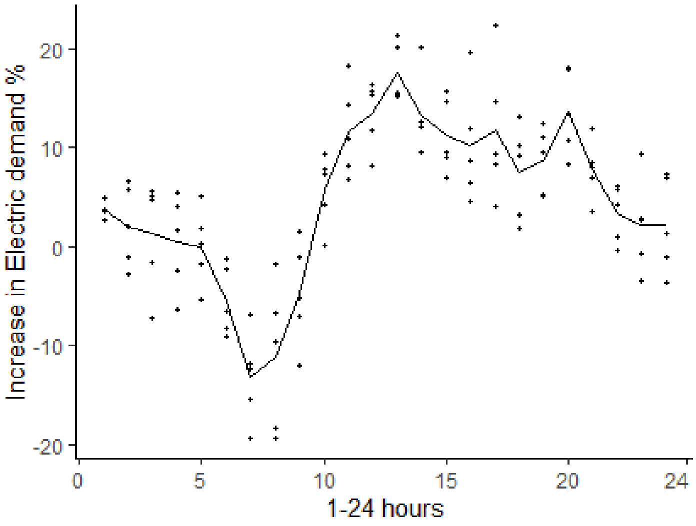


Figure 3.30. Average consumption variations, from AMI

1. Bin daily consumption for working days between 9am and 5pm, for week 1 and week 2.
2. Estimate a percentage X of clients at WFH with an Y increase in electricity consumption.
3. Model all clients at WFH with the same incremental consumption and reframe the week 1 distribution curve with the new X and Y parameters.
4. Calculate the Kullback-Leibler divergence (KL) or relative entropy between the so obtained distribution and the COVID19 registered one.

Point one led to the obtaining of the two curves shown below. The blue curve represents binned daily consumption (KWh) between 9am and 5pm for the week 1. The orange curve instead show the distribution curve obtained from week 2. It shows again a shift towards higher consumptions of an unknown percentage of customers.

The calculation of the Kullback-Leibler divergence was performed by normalizing binned value of consumption and so obtaining a probability distribution curve. For the probability distribution curve of week 2 was at each iteration calculated the KL with the new distribution curve obtained varying X and Y. The KL divergence has the following mathematical formulation, where P and Q are the two distribution curves:

$$D_{\mathrm{KL}}(P \parallel Q) = -\sum_{x \in \mathcal{X}} P(x) \log \left(\frac{Q(x)}{P(x)} \right) \tag{3.9}$$

Here is provided as example a table with values obtained from applying the KL divergence method to the Octopus dataset, as a test.

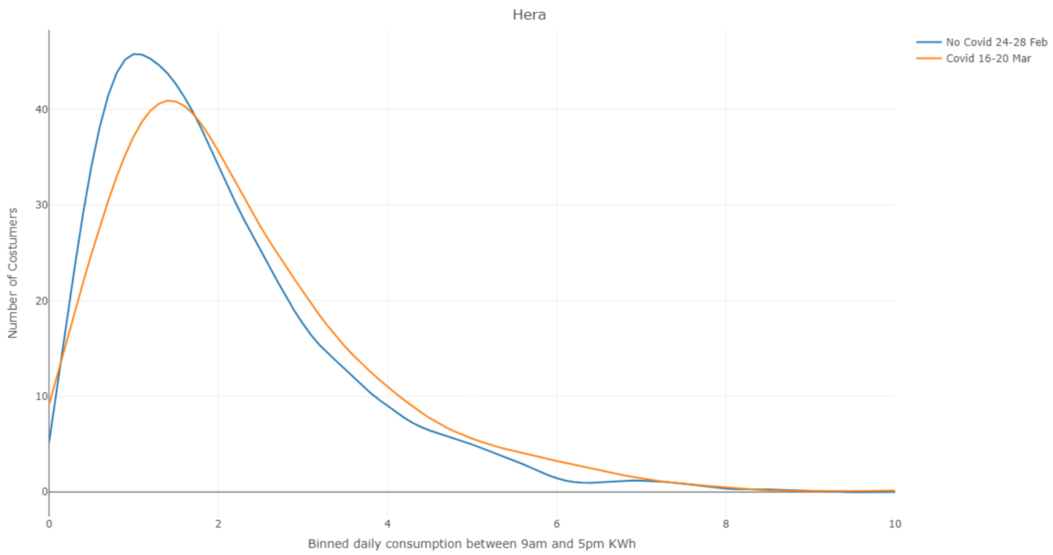


Figure 3.31. Binned consumptions, from AMI

KULLBACK LEIBLER DIVERGENCE

	real	simulated	real	simulated	inf loss
KWh	covid	new clien	P	Q	D(P||Q)
0	750	525	3E-02	2E-02	1E-02
0,5	1250	890	6E-02	4E-02	2E-02
1	1900	1525	8E-02	7E-02	2E-02
1,5	2250	2055	1E-01	9E-02	9E-03
2	2300	2255	1E-01	1E-01	2E-03
2,5	2150	2210	1E-01	1E-01	-3E-03
3	1900	1990	8E-02	9E-02	-4E-03
3,5	1750	1855	8E-02	8E-02	-5E-03
4	1450	1600	6E-02	7E-02	-6E-03
4,5	1200	1320	5E-02	6E-02	-5E-03
5	1000	1105	4E-02	5E-02	-4E-03
5,5	900	990	4E-02	4E-02	-4E-03
6	750	855	3E-02	4E-02	-4E-03
6,5	600	690	3E-02	3E-02	-4E-03
7	500	560	2E-02	3E-02	-3E-03
7,5	450	495	2E-02	2E-02	-2E-03
8	350	387,5	2E-02	2E-02	-2E-03
8,5	300	330	1E-02	1E-02	-1E-03
9	250	272,5	1E-02	1E-02	-1E-03
9,5	200	230	9E-03	1E-02	-1E-03
10	150	165	7E-03	7E-03	-6E-04
10,5	10	45	4E-04	2E-03	-7E-04
11	10	10	4E-04	4E-04	-2E-07
sum	22370	22360	1	1	0,0104

Figure 3.32. KL example on Octopus data

In the next figure is instead shown a 3D plot where on the x label is assigned the WFH level (X) and on the y label the increase in KWh (Y), thus the two parameters varied in the optimization. On the (hidden) zeta axis is instead shown the so calculated KL divergence. Darker colors show convergence toward an optimum area. (minimization of KL). Results indicate about a 20% of clients at WFH consuming around 1-1.5 KWh more each, an increase of about 15%.

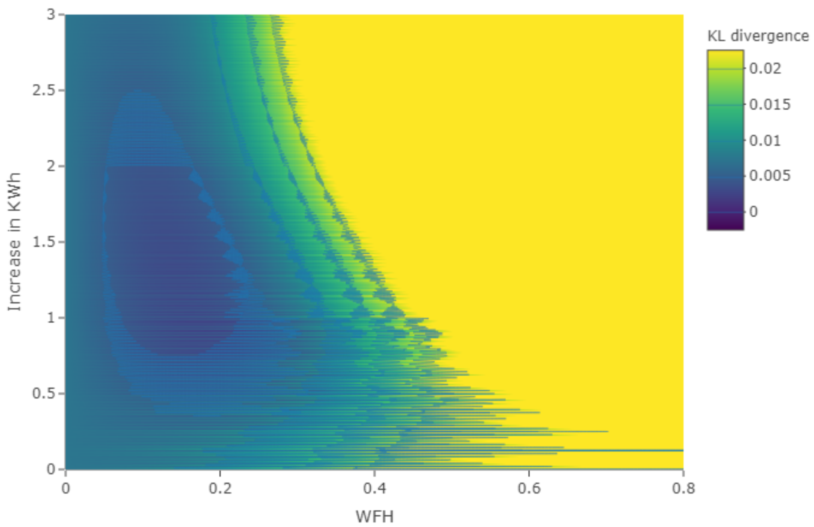


Figure 3.33. KL on AMI data, 100'000 simulations

It was then also applied a method similar to the "consistent increasers" method of Octopus Energy. It consisted in calculating the variations in energy consumption for each costumer (in the previous method it was a binned distribution curve). According to Octopus expected results with this method should be higher than those obtained with the KL method. For each client was calculated the electricity consumed in working week 1 and in working week 2, only in working hours 9am 17pm. Once obtained the variations they were binned. The first "raw" distribution obtained showed that some clients were consuming less electricity than before, an average of the increases would return a +25% in consumption.

An explanation for clients consuming less energy (counterintuitive) could be related to the nature of lockdown, that induced many students and workers to come back with parents/family and leave houses empty. However a contribution to negative consumptions comes also from the switch in working hours showed before, in fact morning hours from 8 to 10 show at least 50% clients having negative changes, as is shown in figure below:

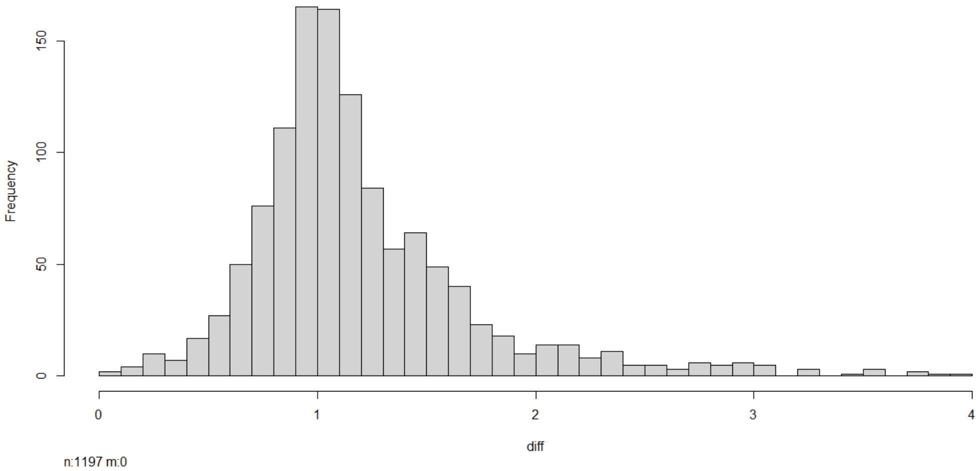


Figure 3.34. Binned consumption variations 9am 17pm

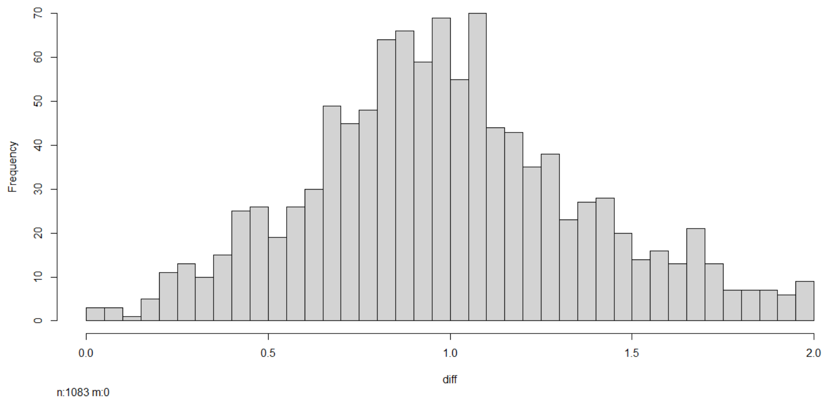


Figure 3.35. Binned consumption variations, 8am 10am

It was thus decided to select only clients showing increases and at the same time not greater than 2.5 (150%), thus excluding 50 clients (4%). Clients showing reductions (cumulative of all working hours of working weeks) where 468. In such a way an average of 687 clients increases equal 37% was obtained. Data from AMI showed therefore a range of possible increases spanning from 15 to 25 to 37%, in a similar way to what obtained by Octopus.

3.5.4 End Use

The collection of data for residential end use variations was less problematic than the one for energy carriers. Literature available was less numerous than for EC, but with the method adopted of verification through the EC-EU matrix, less accuracy was requested. It was thus not required a breakdown of increments between WFH and normal users. The resulting collection of data is provided in the table below, while for two data source a brief explanation is provided.

Table 3.23. EU variations in residential sector

End Use function	Paper/Document	Value	Country
Space Heating	[96, 98, 106]	+15%,+20%,+21%	UK,US,RS
Space Cooling	[102]	+40%	US
Appliances and Lighting	[91, 96, 98, 99, 107]	+25%,+40%(only lights),+3-10%, +7%(all customers),+10%	US,CHN,AU,ES,RS
Cooking	[91, 96, 98, 99] [5, 108, 109]	+50%,+40%, 100% ,+35%	US,CHN,RS,AU
Water Heating	[16, 98, 106]	+15%,25%	UK,RS,SW

The same study presented before, released on “Energy and Buildings” by Cvetkovic D. et al. on October 2020, [98] thanks to the high levels of detail allowed by the EnergyPlus simulation, presented data for variations in End Use due to the higher occupancy in the household. As was mentioned, absolute variations in EC were not deemed reliable due to the presence of local behavior and cultural elements. Yet, for EU it was verified a greater similarity in values with those found in other studies. The study provided the difference in use and final consumption associated with EU at different levels of aggregation, per equipment type, per type of room of the house etc. For example, cooking was provided in the house through the use of an electric stove, with this being the likely cause of EC-Electricity variations being much higher for this study. Energy consumption associated to the electric stove was of 200KWh for a baseline scenario S1 while doubled to 400KWh for a scenario S2 to remain constant independently from the severity of the SIP measures. For this study EU variations where therefore found to be:

Table 3.24. Cvetkovic D. et al

	SH	AL	CK	WH
Variation	21%	10%	100%	25%

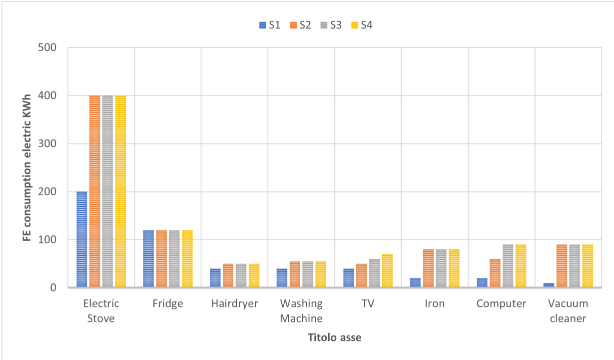


Figure 3.36. End Use variations in an household, Serbia

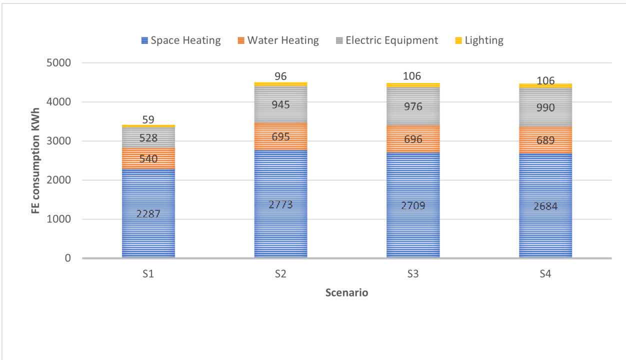


Figure 3.37. End Use variations in an household (2), Serbia

The second study being briefly explained is a research released in July 2020 by Zanocco C et al. of the "Civil and Environmental Engineering department" of Stanford University (US) on "Renewable and Sustainable Energy Reviews". [96] The study titled "Exploring the effects of California's COVID-19 Shelter in Place order on household energy practices and intention to adopt smart home technologies" thus explored the effects of SIP on consumptions and also on change in occupants behaviors. California was the first state to impose COVID19 home confinement restrictions, with the state of emergency declared on March 4 2020. On March 17, the San Francisco Bay Area declared the SIP order which affected around 7 millions residents. The extent of measures deployed was similar to the European ones, and therefore employees started being at WFH (included students and education sector).

To understand the impacts of SIP orders on household occupancy, behaviors and energy profiles, they created a survey regularly filled by a panel of online participants from California. The pool was selected to be the most representative possible. In total they received 804 completed surveys. The study found that increased midday occupancy was associated with respondents who hold a bachelor's degree or higher and households with higher income. This is directly correlated with the parallel US studies performed on the likelihood of WFH, which is directly correlated with education (tertiary) and income levels. The activities with the highest magnitude of change (with over half of respondents signaling more frequent use) were "using a computer, game console, tablet or TV", "cooking with a stov top/range or over" and "communicating by phone or video". Overall variations in EU are reported in the table below. Finding a unique value for AL was not possible as different types of appliances were assigned with their variations. With a rough estimate, considering that dishwasher and washing machines absorb much of an household consumption and were assigned with a variation of less than 25% (in activity), computer and tv with a variations of around 60% and lighting with a variation of 25% a weighted value of around 25,30% should be reasonable.

Table 3.25. Zanocco C et al.

	SH	**AL**	**CK**
Variation	20%	25%-30%	50%

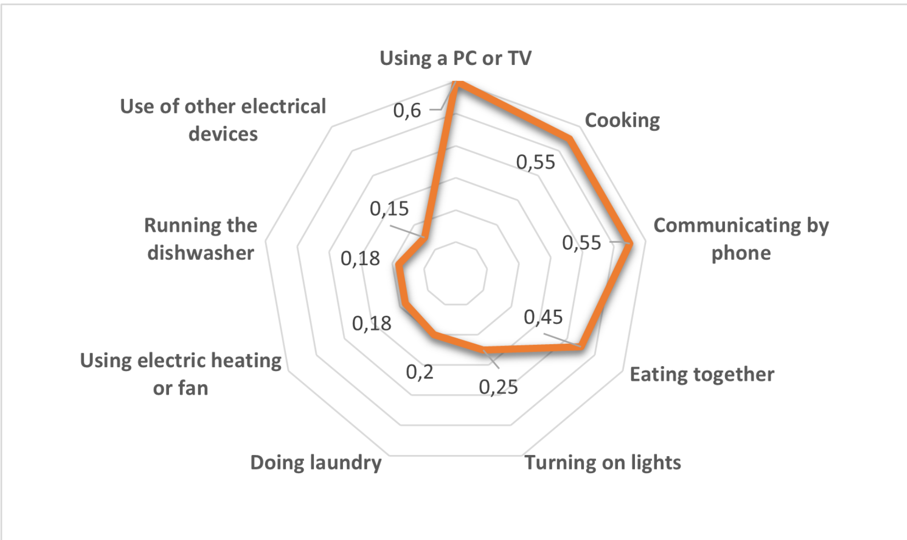


Figure 3.38. End Use variations in 800 homes, California

Finding values for space cooling variations was not easy, as COVID19 lockdowns were in place during winter months of the year. A late research published in December 2020 on "Renewable Energy World" [102] relied on data from "Pecan Street" an energy research utility which has monitored for nearly a decade hundreds of selected homes for research purposes. The 113 houses were located in Texas, US. By performing a breakdown of electricity usages it was possible to identify bizarre changes even in the usage of refrigerators, whose consumptions went up considerably, indicating a more frequent opening of the doors, and thus a more frequent cooking. Energy demand in Austin (Texas) is reported being heavily influenced by air conditioning, even in March, due to temperature swings that can produced significant spikes. However even accounting for such weather swings, data showed that residents were using about 40% more electricity to cool their homes. This data point was the only found for space cooling and inserted in EDGE.

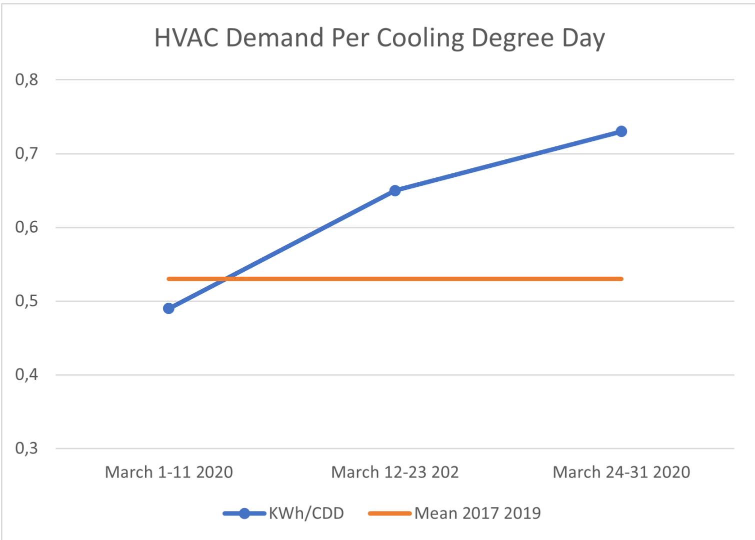


Figure 3.39. Cooling demand variations in 113 homes, Texas

3.5.5 EU-EC Matrix

Overall End Use variations, taken as mean of data found in literature, are shown in the picture below:

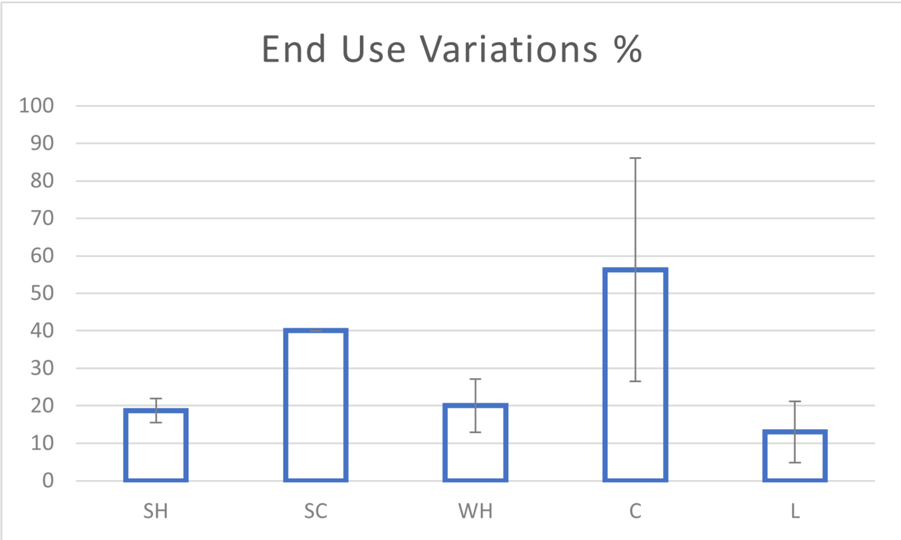


Figure 3.40. End Use variations, mean

End Use variations so obtained were inserted in the EU-EC matrix of UK for the year 2018, obtained from Eurostat. [14, 110] In brief, the choice of UK EU-EC matrix was done so to increase the reliability of outcomes. In fact EC – Electricity (WFH) variations were found for UK and Italy while EC – Gas (WFH) variations only for UK. Moreover the choice of UK is congenial as Electricity and Gas are by far the most used EC (almost 90%), with Cooking EU accounting for around 3% of End Use FC, SH for 63% and AL for 17%. This means that the great uncertainty on cooking demand will not affect results on the EU-EC matrix while instead SH and WH needs more accuracy. The structure of an EU-EC matrix is shown below, where the sum of all elements is one:

$$\sum_{ij} a_{ij} = 1 \tag{3.10}$$

By applying an increment in EC – Electricity of 22% and of 20% for Gas, and a vector of EU changes shown before, but with an high range AL variation of 20%, the mean error on Electricity and Gas consumption is of 0.15%. The sensitivity of Electricity is low, for example changing its value to 40% returns a mean error of 7%. The one of Gas is a bit higher. Varying EU instead the error does not increase

	Electricity	Solids	Heat	Natural Gas	Liquids	Share End-Use
Space Heating	a_{11}	a_{12}	a_{13}	a_{14}	a_{15}	EU1
Space Cooling	a_{21}	a_{22}	a_{23}	a_{24}	a_{25}	EU2
Appliances and Lighting	a_{31}	a_{32}	a_{33}	a_{34}	a_{35}	EU3
Cooking	a_{41}	a_{42}	a_{43}	a_{44}	a_{45}	EU4
Water Heating	a_{51}	a_{52}	a_{53}	a_{54}	a_{55}	EU5
Share Energy Carrier	EC1	EC2	EC3	EC4	EC5	1

Figure 3.41. EU-EC Matrix

significantly. Overall the combination of EC and EU variations seems to be quite stable and robust to perturbations (if a maximum error range of plus or minus 10% is considered acceptable, and given the uncertainties mentioned before it certainly is, according to this research).

3.6 Final Equations in EDGE

Here are presented the final End Use equations as inserted in EDGE, summarizing the advancements:

1. Separation of Residential and Commercial sector through coefficients region, year and EU specific.
2. Separation of the Commercial part through a subcommercial WFH coefficient which was found to be overall constant over years and was therefore assumed independent from regions and years. The average value for this coefficient was of about 0.55
3. Adding of a subcommercial WFH energy savings curve, it is dependent on WFH potential and therefore the values it returns are region and year specific.
4. Calculation of the WFH potential through DN and DN-World Bank. Being dependent from GDP per capita and IIASA population and educational profiles it is region and year specific.
5. Calculation of the share of total population at WFH by multiplying WFH potential by the ETP-WP ratio. ETP brings a region dimension while WP both a region and year dimension. Overall ETP-WP is thus region and year specific.
6. Adding of Residential End Use variations. They are assumed to be constant in time and region, indeed a strong assumption as some efficiency and behavioral WFH induced improvements could manifest in the future, but considering the pilot nature of this study the assumption was valuated overall acceptable.

Separation Residential Commercial:

$$shareAL = \frac{share_{appliances} \cdot FC_{appliances} + share_{lighting} \cdot FC_{lighting}}{FC_{appliances} + FC_{lighting}} \tag{3.11}$$

Coefficient of subcommercial WFH energy savings, with the first two equations being respectively the COVID19 calibration curve and the logistic future curve, and the third one the final:

$$coefCM = 0.27 \cdot WFH \tag{3.12}$$

$$coefCM = \frac{1}{1 + e^{-0.12(x-0.5)}} \tag{3.13}$$

$$coefCM = 0.27 \cdot WFH + \alpha \cdot (\frac{1}{1 + e^{-0.12(x-0.5)}} - 0.27 \cdot WFH)/N \tag{3.14}$$

Coefficient of WFH potential, DN is interpolated and has a "value" dependent on GDP per capita. This "value" is then inserted in the equation below to be corrected with the World Bank method:

$$coefWFH_{scen,reg,yr} = \sum_{i=1}^{20} value_{scen,reg,yr} \cdot coefSD_{reg,i} \cdot coefSSP_{scen,reg,yr,i} \tag{3.15}$$

$$coefSD_{reg,i} = 1 + \frac{1}{2} \cdot erf(\frac{coef}{\sqrt{2}}) \tag{3.16}$$

$$coefSSP_{scen,reg,yr,i} = \frac{population_{scen,reg,yr,i}}{population_{scen,reg,yr}} \cdot \tag{3.17}$$

Coefficient of ETP-WP multiplied by the coefficient of WFH potential:

$$ETP_{reg} = \frac{Employed_{reg}}{WorkingPopulation_{reg}} \tag{3.18}$$

$$WP_{scen,reg,yr} = \frac{Population_{\ aged\ 16-64,reg,yr}}{Total\ Population_{reg,yr}} \tag{3.19}$$

$$WFH_{scen,reg,yr} = coefWFH_{scen,reg,yr} \cdot ETP_{reg} \cdot WP_{scen,reg,yr} \tag{3.20}$$

The general structure of an End Use such modified equation is the following, with $\zeta(q_1)$ being the old End Use function, q_1 representing the default set of variables, $\gamma(q_2)$ the new End Use function and q_2 representing the new set of variables (eg. shareEU etc):

$$\gamma(q_2) = \gamma(q_{2,res}) + \gamma(q_{2,comm}) \tag{3.21}$$

$$\gamma(q_{2,res}) = \zeta(q_1) \cdot shareEU_i, reg, yr \cdot (1 + WFH_{scen,reg,yr} \cdot \Delta_{EU,i}) \tag{3.22}$$

$$\gamma(q_{2,comm}) = \zeta(q_1) \cdot (1 - shareEU_i, reg, yr) \cdot (1 - 0.55 \cdot coefCM_{scen,reg,yr}) \quad (3.23)$$

Chapter 4

Results

This chapter is so organized. First in section 4.1 is presented the sensitivity analysis performed on the new model's input. Then in section 4.2 is dedicated to the Monte Carlo simulation and its results. In section 4.3 are presented results from similar studies and a COVID19-lockdown simulation.

4.1 Sensitivity Analysis

In the WFH modified EDGE model was introduced a considerable amount of new variables, and almost each was bringing its related uncertainty. The only variable for which it was not possible to determine a probability distribution was the residential share, obtained from the IEA ETP 2017. In fact in the official documentation no indication was provided for it. Prior of the Monte Carlo analysis a sensitivity check was however performed on the output, to figure the dynamics involved around parameter's uncertainties. Some considerations can be made:

- Expectations are that higher the level in the original equation, in which the variable was introduced, higher should be its sensitivity for the output. As an example, the commercial and residential separator, which splits the equation in two parts, should affects greatly the result, because there are no other coefficients dampening its variations. At the contrary, variations on the increments of residential consumptions are expected to have a lower impact profile, being at the lowest level in the equation.
- The only coefficients involved in nonlinear behavior should be the one affecting the subcommercial energy savings curve, namely the coefficient of WFH potential. In fact, for how it was built, positive variations on the function input (WFH potential) should be reflected in higher general model output with respect to reductions of its input (the curve was a logistic one). Instead, all others coefficients should show symmetric effects between increments and decrements.

Coefficient of Commercial Residential separation: an increase in this coefficient should affects strongly the result, toward greater consumptions, being given more weight to the residential sector.

Coefficient of WFH potential: an increase of the potential of work from home affects both the energy savings in the subcommercial sector, in a positive way, and the number of people at WFH, thus increasing residential consumptions. The net effect depends on the others coefficients and can not be established a priori. As mentioned before, it is the only one that should have a nonlinear behavior.

Coefficients ETP-WP: in increase in this group of coefficients should result in higher level of residential consumption.

Coefficient of subcommercial reduction: the choice of the subcommercial reduction curve is modeled in EDGE through the multiplication of the previously showed equation by a parameter N, where N equal 50 returns the pure logistic equation, while N equal 0 returns the baseline linear equation calibrated amid COVID19 pandemic. An increase in the parameter N therefore imply higher levels of energy savings.

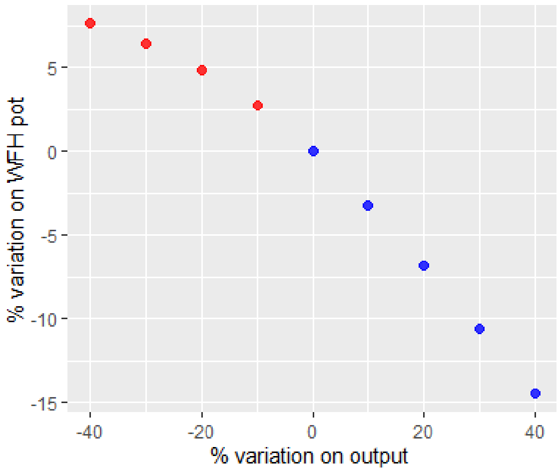
Coefficient of subcommercial separation: by increasing the parameter toward values closer to the one predicted by the WIOD-NAMEA method, should be the weight of the commercial WHF subsector higher and therefore overall energy savings should be higher.

Coefficients of residential increase of consumption: an increase in these values result in increasing residential consumption.

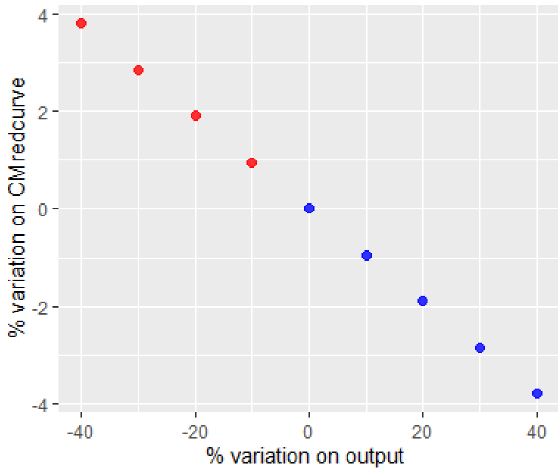
Others: For the coefficients included in the DN-World Bank method and for other minors implemented in the code was not performed a sensitivity analysis. For instance, the shape of the DN-WFH curve was not modified, assumptions relative to the IEA-EDGE regional mapping could also affects the model's result. The EDGE region of Africa was in fact assigned with the IEA World average region, but that caused some discrepancies on the assignment of the shares of space heating and water heating. Trends for this region should be closer to the one of other developing-mid latitude regions such India.

The sensitivity analysis was thus performed in a simple but still efficient way. The predicted absence of strong non linearities justified an easy approach. It was built a matrix where the j columns represented the new coefficients and nine rows represented variations in absolute value spanning from +40% to -40%. Each value of the 9x10 matrix was an input point for the algorithm. In total 90x5 (5 SSPs) iterations were performed. The output was defined as the sum of all years 2020-2100 world total variations in Final Energy Demand. Possible undulating behavior could not be registered with such an output formulation, however a prior group of runs showed that "net energy variations" curve were showing almost pure monotone trends.

Results showed that the commercial residential separator is the coefficient impacting most on results, with variations of its value of 40% impacting up to 100% on the results in the SSP5 scenario. In all other scenario instead the ratio was more of 1:2 (20% variation on the results for 40% on the input) or 1:4 (10%). Of all others coefficients, the group of residential end use variables was the one impacting less on the results with maximum variations of 3-5% on the output for 40% variations in the input. The group of WFH, commercial reduction variables instead showed stronger effects. The coefficient of WFH potential in primis along with the subcommercial separator. In



(a) Nonlinear effects, WFHpot



(b) Linear effects

Figure 4.1. Different effects of variable's uncertainties

the SSP5 scenario variations for these two coeff. of 40% produced perturbances up to 60%. In the SSP4 of about 15% while for the other scenario were less than 5%. As predicted, the WFH potential effects are asymmetrical, with increments resulting in overall decrease of Global Final Energy consumption. This means that translating vertically the WFH potential curve (therefore increasing values of WFH potential but not modifying the shape of the function) have more effects on energy savings than what a decrease of WFH potential would have on energy increases. In the picture below are taken two example from the SSP1 scenario showing the nonlinear behavior for WFH potential and the linear one for the other (it was chosen to show the subcommercial energy saving coeff.)

4.2 Results with Monte Carlo

4.2.1 Simulation settings

A Monte Carlo analysis by definition "*perform uncertainty analysis by building models of possible results by substituting a range of values - a probability distribution – for any factor that has inherent uncertainty.*" It was chosen not to vary the commercial residential separation for two main reasons:

1. Its related uncertainty was unknown.
2. Due to its large sensitivity on outputs, it would shadow most of the effects caused by other's variables variations.

The range chosen for the standard deviations was based on assumptions made on the nature of data points and on their original distribution. As example, cooking had a related high uncertainty, some data showed a 100% increase while others 50% or less. It was thus assigned a mean of 50% but with an higher SD of 5. The probability distribution profile was set to be a normal one, in absence of better alternatives.

Here is shown the set of inputs and related uncertainties provided to the model, and below a representation of the probability distributions:

Table 4.1. Monte Carlo settings

Variable	**Mean**	**Standard Deviation**
Space Heating incr.	20	2
Space Cooling incr.	40	2
Appliances Lighting incr.	15	2
Cooking incr.	50	5
Water Heating incr.	20	2
WFH pot var.	1	0.2
ETP-WP var.	1	0.1
Subcomm sep. var.	0.55	0.05
Subcomm red. var.	25	8

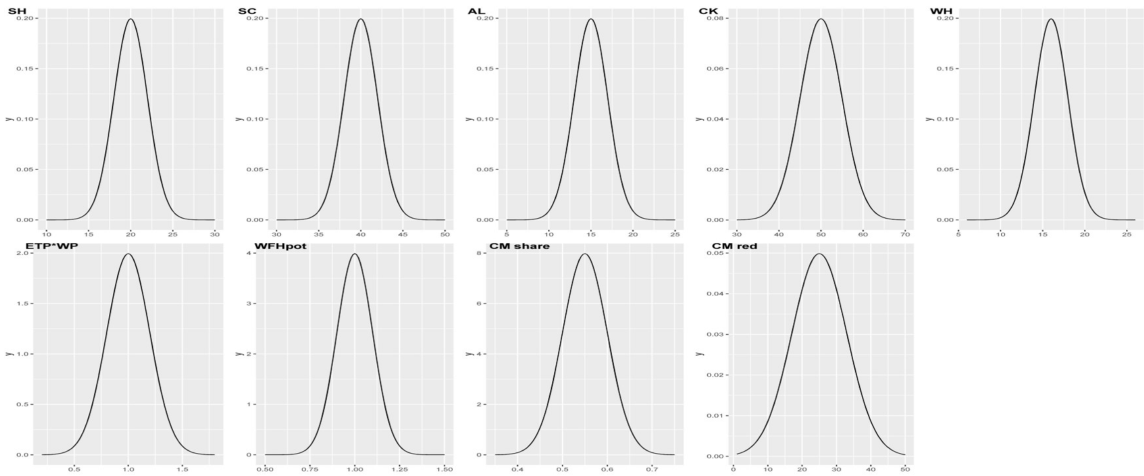


Figure 4.2. Probability distributions

Due to the large number of physical memory required for the Monte Carlo simulation (between 10million-50millions rows) an optimum amount of 60 simulations was found. Results did not vary much over that level.

4.2.2 Results - SSP

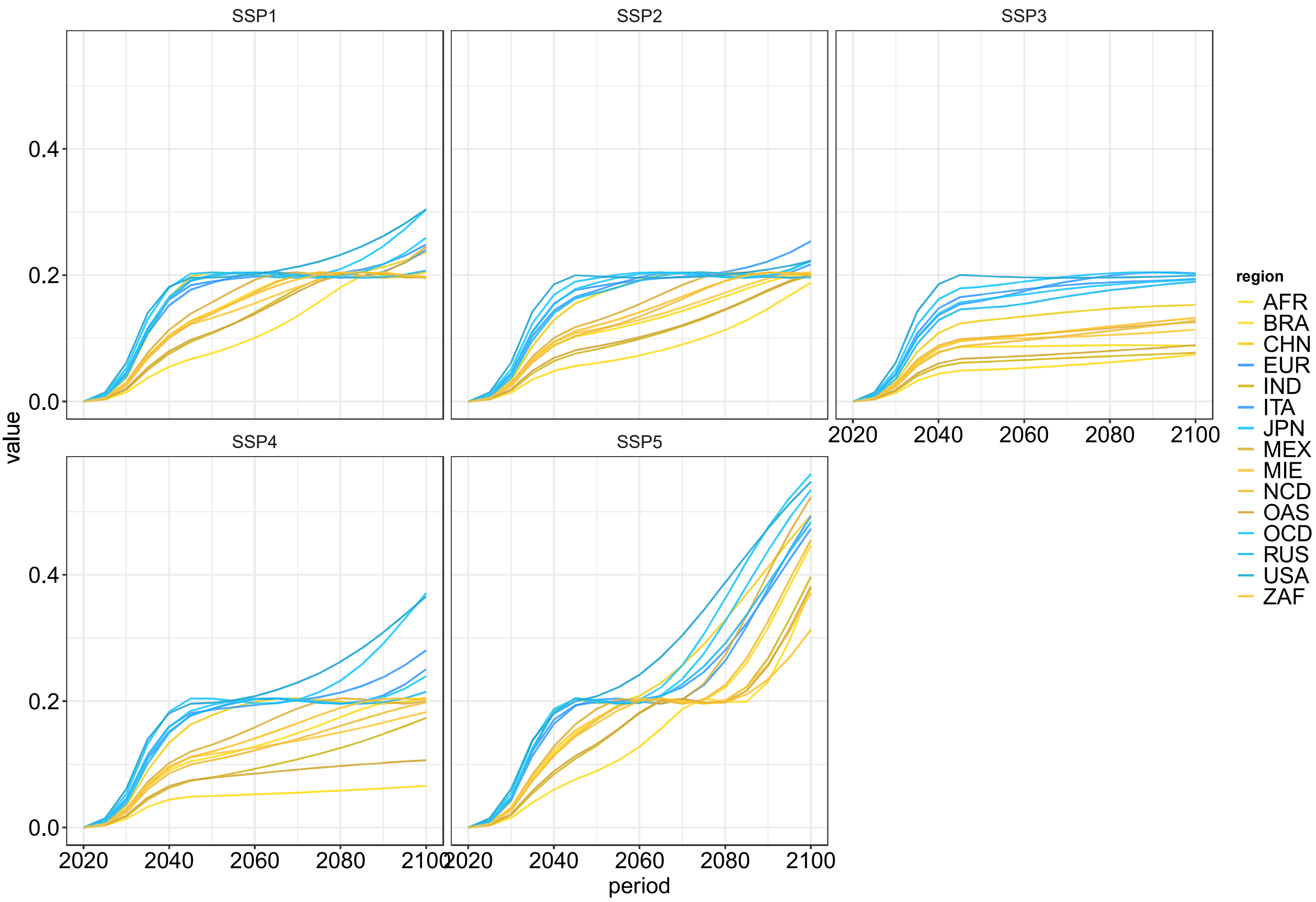
In this section are discussed the results of the Monte Carlo simulation, which number of runs was set to an optimal value of 60. Higher numbers did not significantly change the quartile distribution of results. Plots are shown with uncertainty bars for the most important variables.

1. A line represents the mean of all values.
2. A darker area surrounding the mean show values between the second and third quartile. (50% of all values)
3. A lighter external area shows the values between the first and the second quartile and between the third and the last quartile. (remaining 50% of all values). The area between the second and third quartile is extremely thinner than the outer one.
4. In regional plots, each line is the mean of N Monte Carlo simulations. Their relative uncertainties are not shown for sake of clarity at a regional level of aggregation. Uncertainty bars in global plots are thus not to be misunderstood as representing the space for regional variations. For example, Net Changes in the Residential sector in the SSP1 have a max. 4th quartile line reaching 6%, while in the regional plot the maximum increase shown is of 5%.

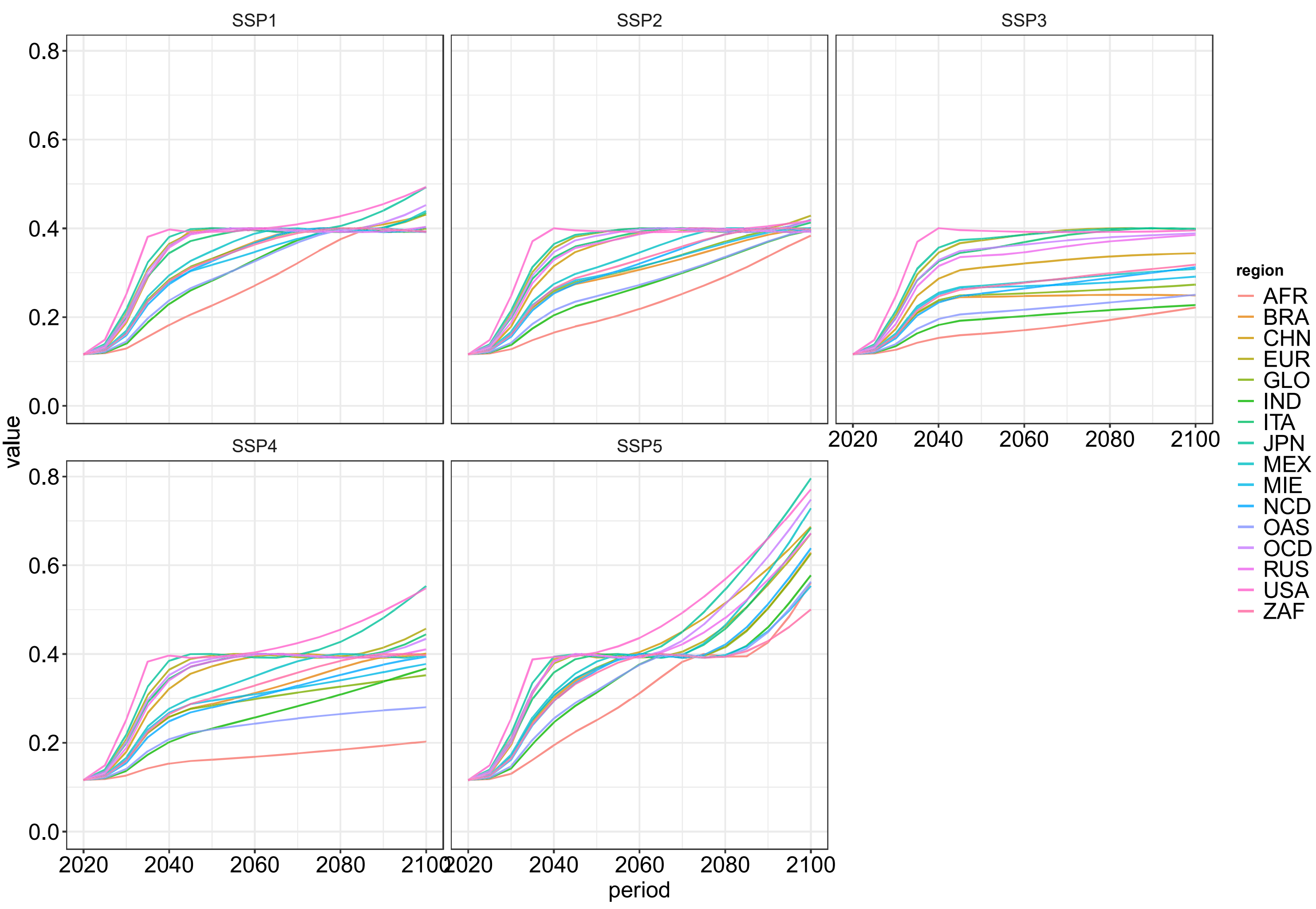
The uncertainty distributions tend to increase in absolute amplitude with time. This trend was expected and is due to the mathematical definition of some of the newly added equations, for example the subcommercial reduction curve which has a logistic behavior and the WFH potential which increase nonlinearly with GDP per capita. Results are showed for each SSP, in order. First are shown in the next page the results of the coefficients of commercial reduction, then is made a recap of the specifics of each SSP, how drivers of Final Energy behave differently according to the scenario narratives. Then variations of Final Energy are commented.

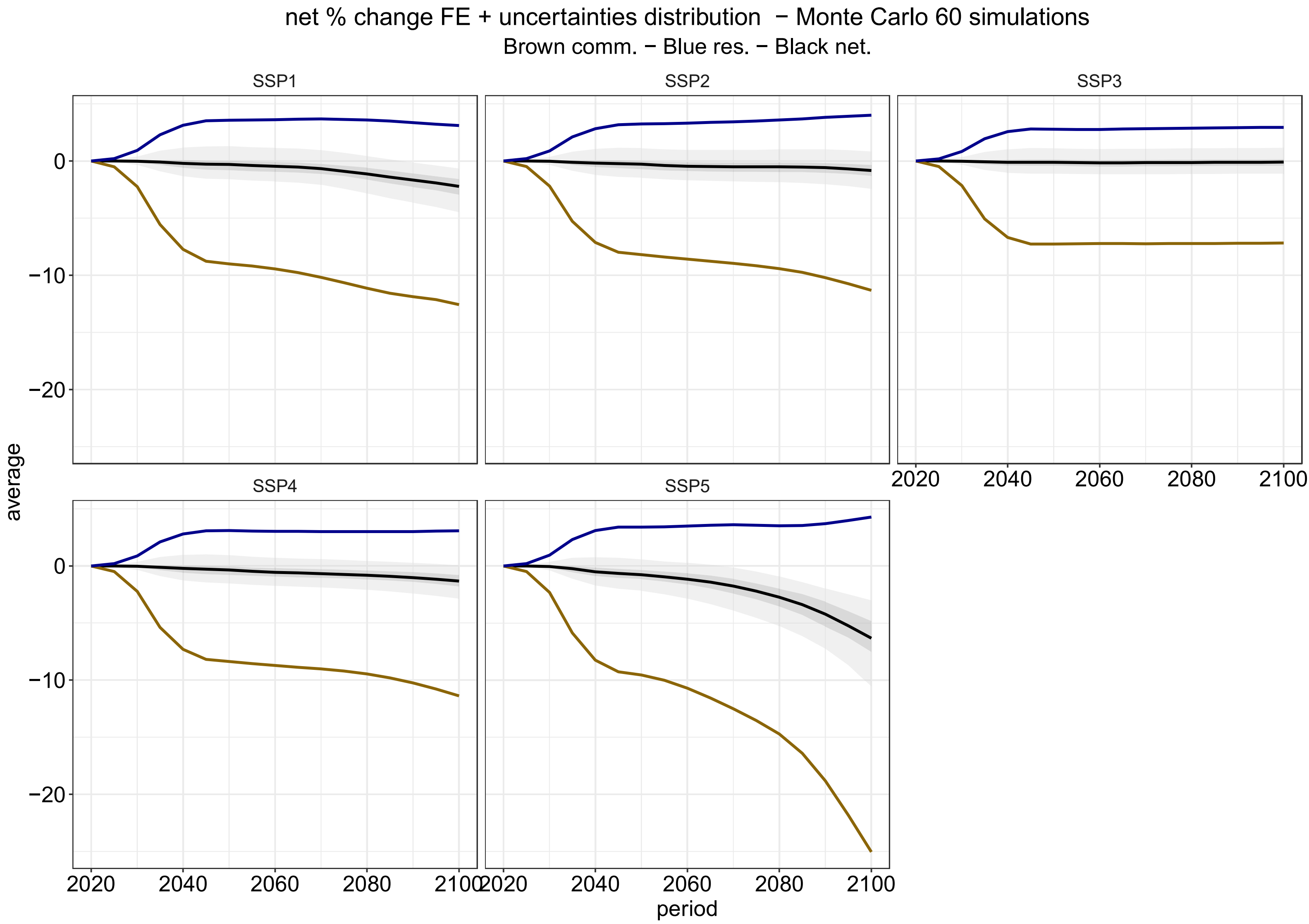
For a complete review of the behaviors of the Residential – Commercial shares it should be consulted Chapter 3, section 2.3. For instead a review of the SSP scenarios' definitions should be consulted Chapter 2, section 2.2.

coeff COMM reduction − Developed Developing − Monte Carlo 60 simulations



WFH potential % employed persons, DINGEL NEIMAN (mean)

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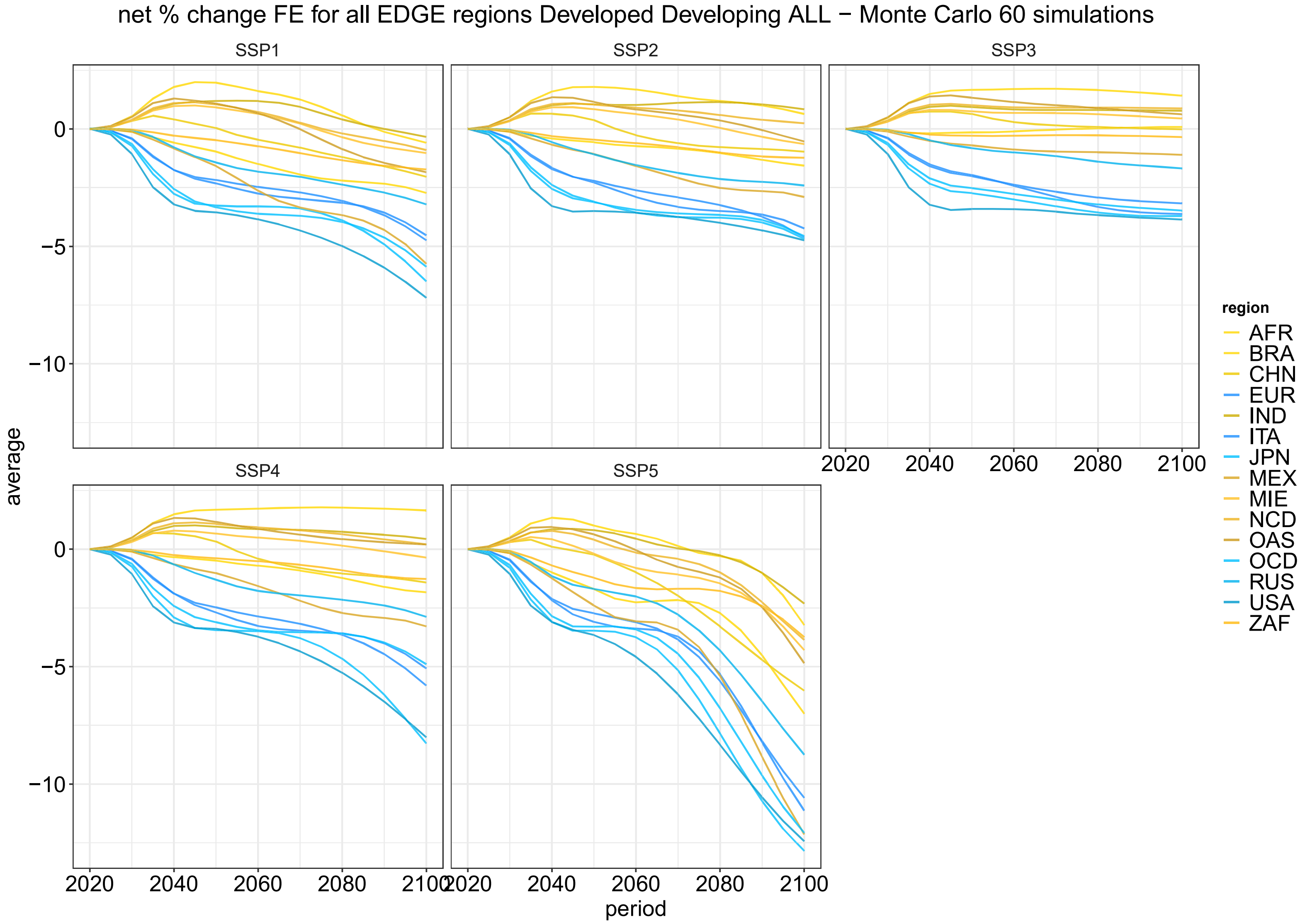
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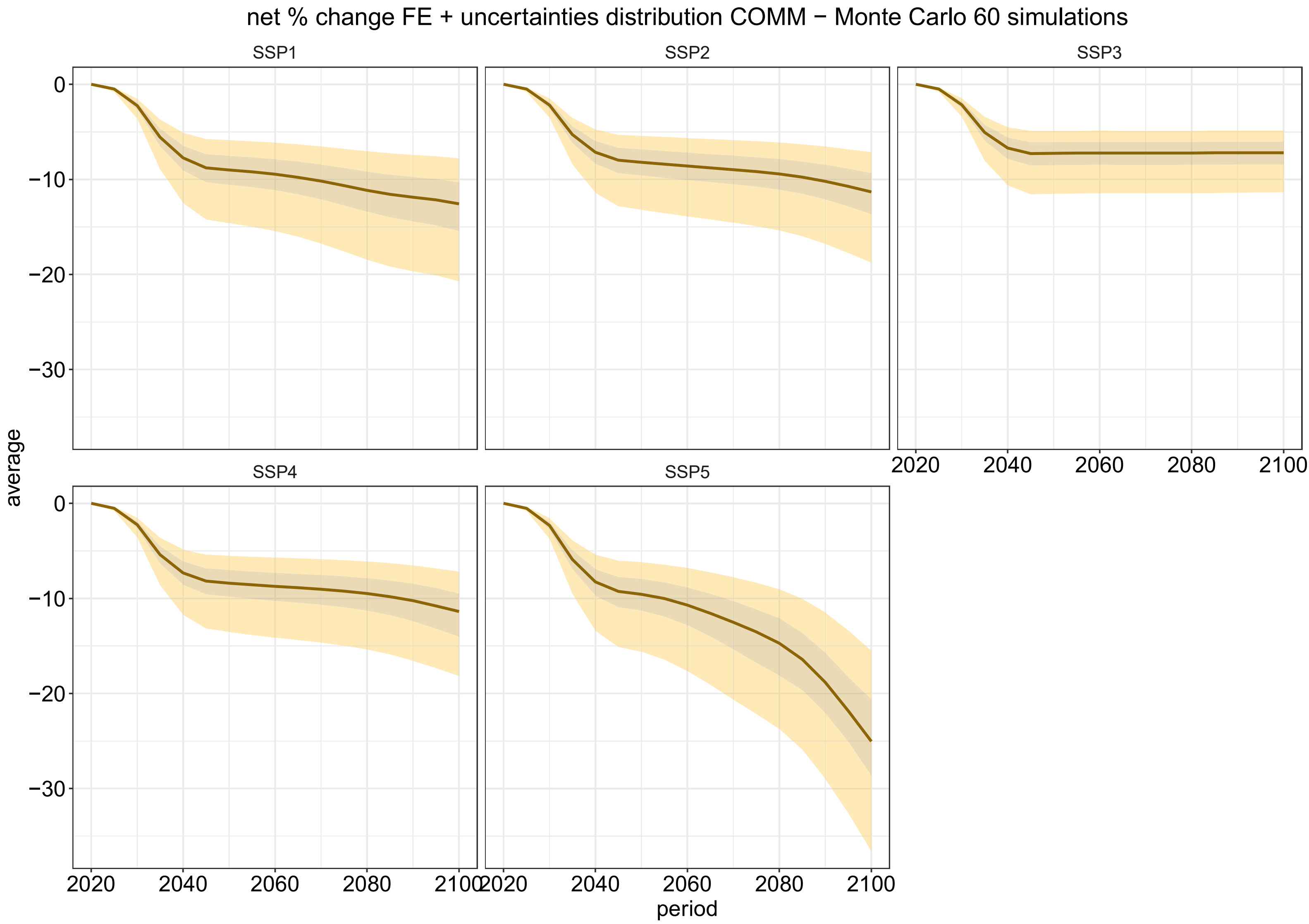

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SSP3
SSP4
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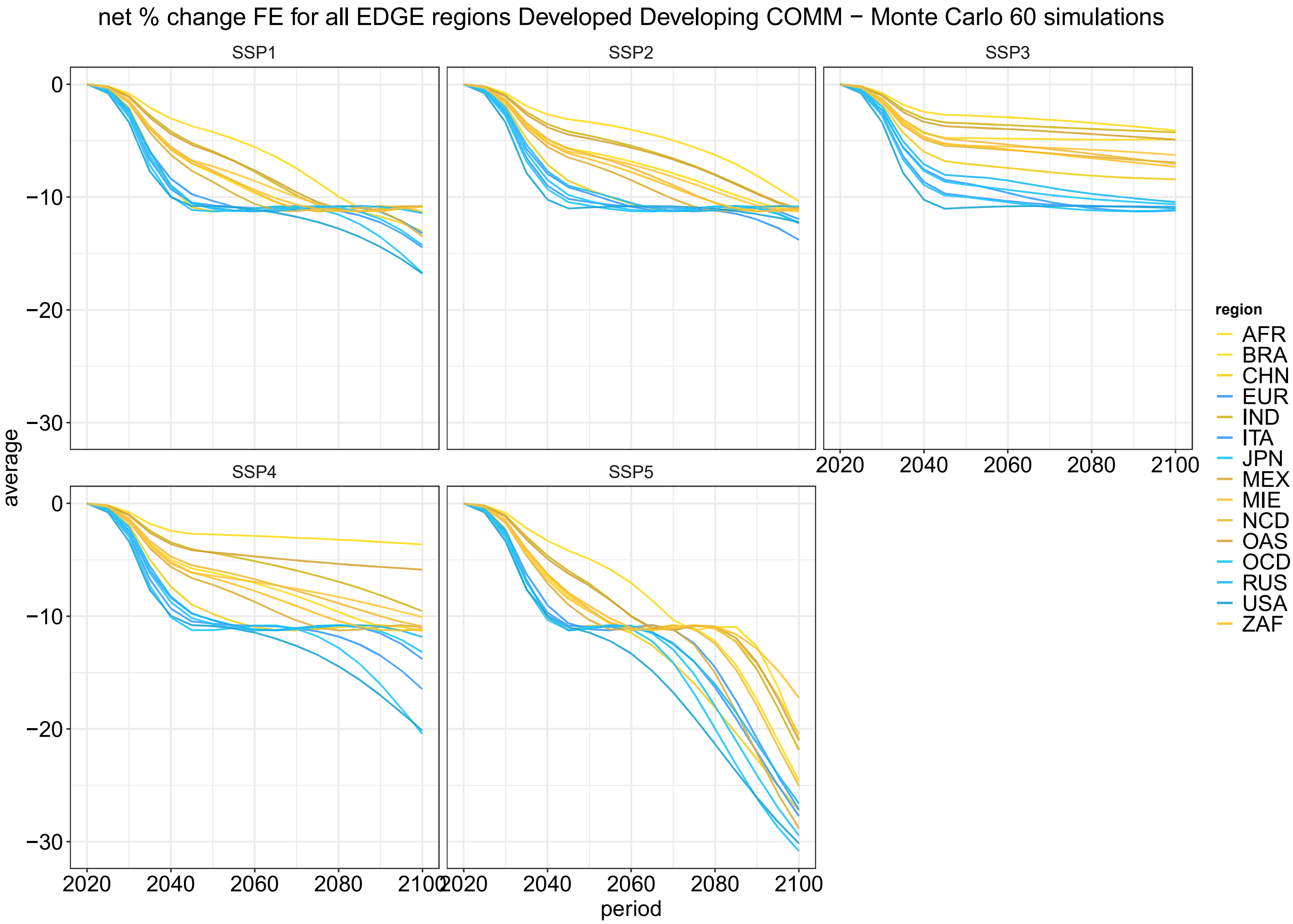
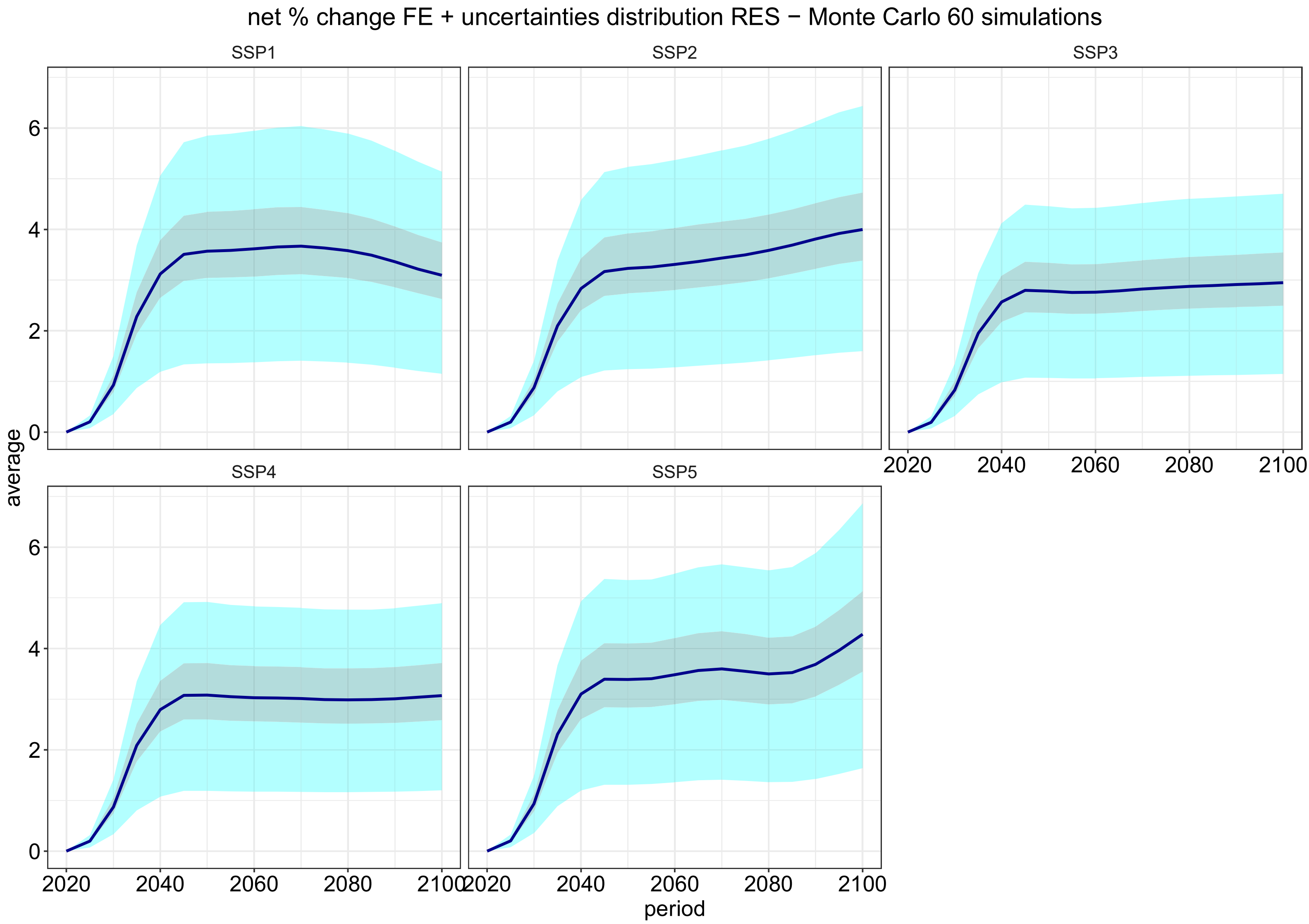
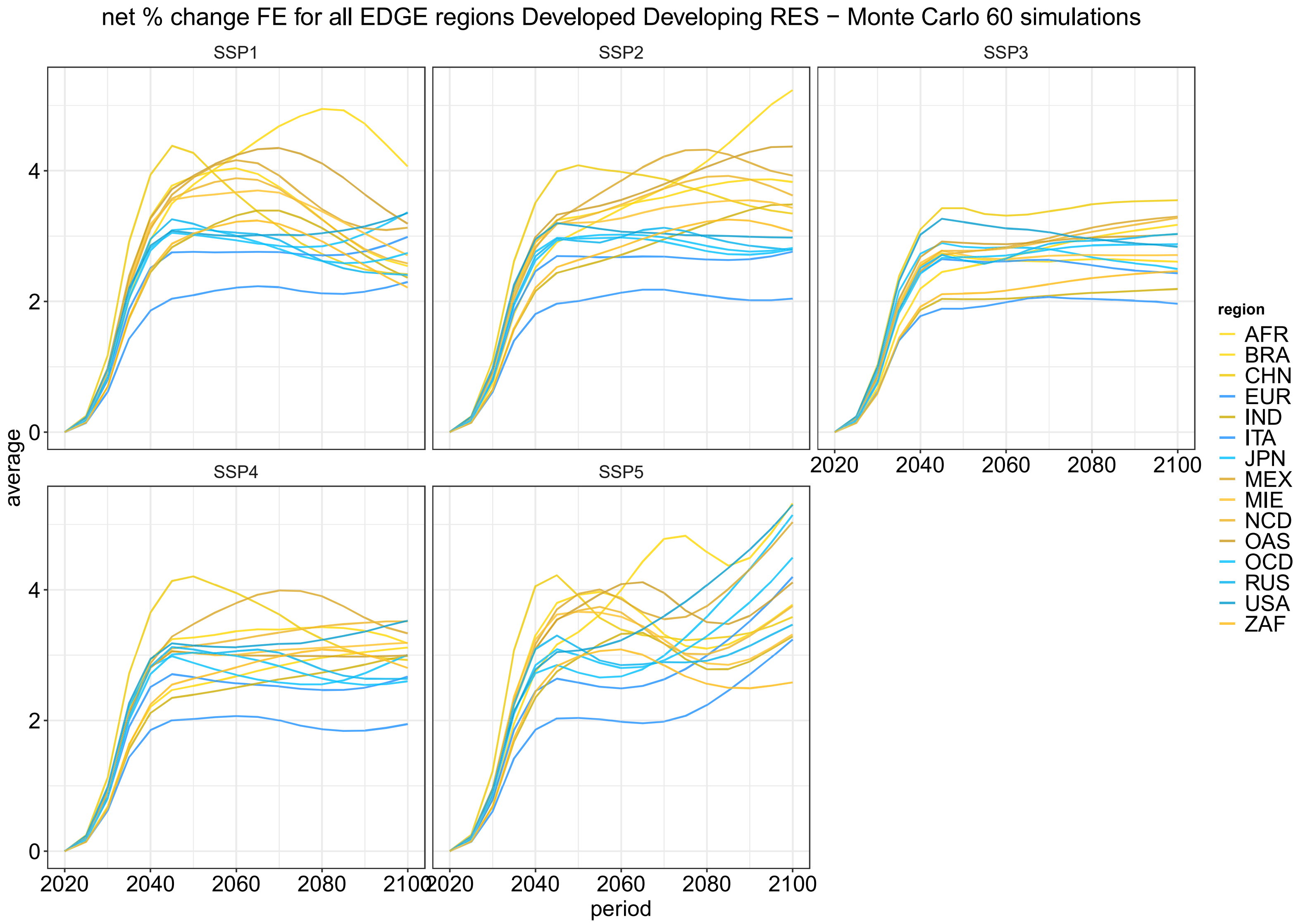
2060
2080
2100



net % change FE for all EDGE regions Developed Developing COMM − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period
0
−10
−20
−30
2020
2040
2060
2080
2100
region
AFR
BRA
CHN
EUR
IND
ITA
JPN
MEX
MIE
NCD
OAS
OCD
RUS
USA
ZAF


net % change FE + uncertainties distribution RES − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period
0
2
4
6
2020
2040
2060
2080
2100


net % change FE for all EDGE regions Developed Developing RES − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period
0
2
4
2020
2040
2060
2080
2100
region
AFR
BRA
CHN
EUR
IND
ITA
JPN
MEX
MIE
NCD
OAS
OCD
RUS
USA
ZAF

SSPs Final Energy variations %			
	Scenario	2050	2100
Net	SSP1	0 (-1 to 1)	-2.5 (-5 to 0)
	SSP2	0 (-1 to 1)	-1 (-2 to 1)
	SSP3	0 (-0.5 to 1)	0 (-0.5 to 0.5)
	SSP4	0 (-1 to 1)	-1 (-2.5 to 0)
	SSP5	-1 (-1 to 0)	-5 (-10 to -3)
Residential	SSP1	3.5 (1.5 to 6)	3 (1 to 5)
	SSP2	3.2 (1.2 to 5)	4 (1.7 to 6.4)
	SSP3	3 (1 to 4.5)	3 (1 to 5)
	SSP4	3 (1.25 to 5)	3 (1.25 to 4)
	SSP5	3.5 (1.5 to 5.3)	5 (1.8 to 7)
Commercial	SSP1	-8 (-14 to -5)	-12 (-18 to -7)
	SSP2	-8 (-12 to -5)	-11 (-18 to -7)
	SSP3	-7 (-11 to -5)	-6 (-11 to -5)
	SSP4	-8 (-14 to -5)	-11 (-18 to -7)
	SSP5	-10 (-15 to -6)	-25 (-36 to -15)

Figure 4.3. SSPs results

4.2.3 Subcommercial reduction results

Observing the trends for the coefficient of commercial reduction it is clear the similarity with those for the WFH potential. The two coefficients were shown in the same page to facilitate a comparison. Different behaviors start to show up whenever the level of about 40% WFH are exceeded. This happens due to two reasons:

1. The interpolation for WFH potential had a null derivative for levels of WFH 40%, only to increase again for higher values of GDP per capita.

2. The curve of commercial reduction was constructed by adding to the COVID19 calibrated savings curve (worst case scenario) an optimistic "future" savings logistical curve. For levels of WFH lower than about 40% "future" curve's values are only about double the value of the "baseline" curve, while for higher levels of WFH the logistic curve's strong increase starts to dominate and levels of the "future" curve are three or four times higher than the "baseline". For a WFH potential level of 40% the worst case curve predicts only reductions of about 10%, the best case about 30%, the median of 20%. Therefore explained values for the coefficient of commercial reductions of about 20% maximum.

Levels of WFH higher than 0.4 are rarely reached or exceeded by world regions, a part in the SSP5 scenario and for periods near the end of the century, hence the logistic behavior of the coeff. commercial reduction is scarcely displayed. Reductions in building consumptions of about 20% for levels of unoccupancy (WFH) of 40% is already a considerable progress with respect to registered COVID19 reductions of 20 to 30% for levels of unoccupancy of 80 to 100%. Yet, a more accurate characterization of energy savings buildings performances would require separate curves for different types of subcommercial buildings. In fact input levels of WFH potential are an average of the full subcommercial sector (public buildings, services, educational etc.), but as was shown in chapter 3 section 3.2 "Subcommercial separation", some subsectors have, on average, much higher levels of WFH potential, as for example offices, which values are of about 80% for the US. According to the logistic curve, they could experience reductions of up to 80% for equal levels of unoccupancy. This level of detail yet is not implemented.

Other effects that could impact the commercial reduction curve but were not implemented are:

1. As was introduced in the WFH chapter, human needs for social interactions must be considered when analyzing remote work phenomena. A trend which was registered in the last years, in parallel with the adoption of WFH, was the disposal of common offices for coworking, were employee of different companies could combine the benefits of avoided commuting (an employee can choose the nearest coworking facility) with those coming from social interactions. The adoption of coworking space could be allocated as a "virtual" increase in residential consumptions, if increases in consumption are similar to the residential ones, or more likely as increases in the commercial sector. Much thus depends on the levels of energy efficiency of coworking facilities compared to the standard commercial ones. One could image that due to the more rigid energy efficiency regulations in place new coworking facilities should be less energy intensive than old work places and therefore overall consumption should still decrease.

2. Commercial workplaces could foresee a decrease in floor space area as high WFH levels become structural. The effects of this phenomena on the model are yet to be assessed but are expected not to be high.

4.2.4 SSP1 results

The SSP1 scenario - "Sustainability" forecast a reduction in inequalities within and across nations, the World follow an inclusive development path.

GDP per capita: After SSP5 and SSP4, SSP1 is the scenario forecasting the highest GDP per capita increases, with levels comparable with the SSP4 scenario but with a much higher convergence between developing and developed countries. In fact, after SSP5 it is the scenario forecasting the strongest income convergence in 2100. By the end of the century nations show income per capita levels differentiating by a maximum of 15% from the mean, with starting values of around 100%.

Tertiary education levels: SSP1 is, along with SSP5, the scenario forecasting highest education levels. By 2050 from 20 to 30% of world population is projected to attend universities or specialization centers. A great convergence between developed and developing countries is projected. This is consistent with the SSP1 narrative, which project high investments in education and health sectors.

ETP-WP ratios: ETP-WP ratios are the product of a country specific employment index, which is assumed constant over years, with the share of working population WP country and year specific. Hence temporal trends are consequence of the WP evolution over years. The SSP1 scenario forecast a strong reduction of the share of population aged 16 to 64, with values for developed countries ranging from levels of 25% in 2020 to 15% in 2100, while developing countries show decrease from values of 30 to 50% in 2020 to about 20% in 2100. This is consistent with the SSP1 narratives, which foresee in particular for developing countries a demographic transition toward more “balanced” population, similar in composition to the one of developed countries. In other words, as life expectancy increases and fertility decrease, the share of population aged more than 64 years increases, while the share of those aged less than 40 years decreases. In fact the same trend can be observed for the SSP5 scenario.

WFH potential: According to Dingel Neiman method, which depends on GDP per capita, the SSP1 and SSP5 scenario are the ones experiencing highest shares by 2050 due to a great economic growth. Moreover in the SSP1 WFH pot. is equally distributed across developed and developing countries, with values spanning from 30 to 40% of employed population. Results from method 2 (DN-WB) are instead more variegate as they depend on educational, gender and age pop. compositions. Yet, a convergence between developing and developed countries towards levels of around 20% can be observed.

WFH total population: Here the trends from WFH potential and ETP-WP ratios mix up. If in fact WFH potential was higher for developed countries, their ETP-WP ratios were lower, with lower shares of population aged 15 to 65. In other words, developed countries have an older population. These two counteracting effects result in similar WFH shares across the world, in the SSP1 scenario. Median values for developed countries are still slightly higher than those of developing countries. Overall from 10 to 14% of world population is expected to be at WFH by 2050.

Coefficient of commercial reduction: thanks to the high levels of WFH potential in the SSP1 scenario, a similar pattern is observed for this coefficient, which depends on the first and as was mentioned in the previous paragraph does not exhibits its logistic nature until levels of WFH pot. higher than 40% are reached.

Final Energy net variations for the Building sector in the SSP1 scenario are globally zero for 2050, while could reach -2.5% in 2100. At a regional level, developed regions experiences net reductions from -2.5 to -5% or more by 2100, while developing regions experience mostly zero or increases up to 2% in the first half of the century to then catch up in reductions (though reduced in magnitude) with developed countries. By 2050 the residential sector should experience an increase of about 3.5%, while the commercial sector a decrease of around 8%. Trends for the residential sector are expected to remain constant throughout the century, while those of commercial sector to decrease up to levels of -12% in 2100. Here are shown only results obtained with the WFH first method (DN). Labeled results for developed and developing countries represent the space of national means and not uncertainties.

SSP1 Final Energy variations %			
		2050	**2100**
Net		0 (-1 to 1)	-2.5 (-5 to 0)
	Net Developed	-3 to -1.25	-7.5 to -2.5
	Net Developing	-1.25 to 2.5	-2.5 to 0
Residential		3.5 (1.5 to 6)	3 (1 to 5)
	Res. Developed	2 to 3	2 to 3
	Res. Developing	3 to 4	2 to 3
Commercial		-8 (-14 to -5)	-12 (-18 to -7)
	Com. Developed	-10	-16 to -10
	Com. Developing	-9 to -4	-13 to -10

Figure 4.4. SSP1 results

4.2.5 SSP2 results

The SSP2 scenario - "Middle of the Road" foresee general socioeconomic trends not diverging much from the present ones.

GDP per capita: In the SSP2 GDP per capita is the second lowest across scenarios, after SSP3. Inequalities in income distribution between developing and developed countries are greater than in the SSP1 but still less than in the SSP3 and SSP4. The group of developed countries by 2100 has average GDP cap. around 40% higher than those of developing countries.

Tertiary education levels: In the SSP2 high education levels show constant increasing trends throughout the century. Developed countries experience increases of about 50% from 2020 to 2100 while developing countries on average about 100% from values of 10% in 2020 to 20% of total population in 2100. The original differences between rich and dev. countries is reduced only slightly.

ETP-WP ratios: Due to the same dynamics involved in the SSP1 scenario, the share of working population (and thus employed) in developing countries reduces to levels of about 30% in 2100. These levels are similar to the ones of the SSP4. Fertility decreases less than in SSP1 and life expectancy increases less.

WFH potential: Levels of WFH, with the DN method, are forecast to increase in a similar way to the SSP1 scenario but with lower maximum levels from 2060. Developing countries reach the "saturation" level of 40% WFH around the end of the century, while in the SSP1 it was reached around the 60s. This is due to the slower GDP cap growth in the SSP2.

WFH total population: The share of total population at WFH ranges from 5 to 15% in 2050, with similar values throughout the century. Developed countries show slightly decreasing trends while developed countries increasing ones. Again, as explained for the SSP1, two counteracting effects are involved. (GDP and aging population)

Coefficient of commercial reduction: Considerations are the same than for SSP1, developing countries have though by 2050 much lower reductions in WFH subcommercial energy with respect to developed countries. The first on average 10% while the second 20%. Commercial reductions for developed countries by 2100 are the second lowest among SSPs. This is due to the much lower GDP cap growth of the SSP2.

Final Energy net variations for the Building sector in the SSP2 scenario are globally zero throughout the century. However strong differences occur between regions. Developing countries have average reductions of 2.5% or more throughout the century while developing countries all experience net increases up to 2% by 2050. Around the 50s the residential sector should experience globally an increase of about 3.2%, while the commercial sector a decrease of around 8%. Trends for the commercial sectors are expected to remain constant throughout the century. Yet the lower range of commercial reduction reach -18 by 2100. Trends for the residential sector instead are projected to increase for developing regions.

SSP2 Final Energy variations %			
		2050	**2100**
Net		0 (-1 to 1)	-1 (-2 to 1)
	Net Developed	-3 to -2.5	-4 to -3
	Net Developing	-1 to 2	-2 to 1
Residential		3.2 (1.2 to 5)	4 (1.7 to 6.4)
	Res. Developed	2 to 3	2 to 3
	Res. Developing	2.5 to 4	3 to 4.5
Commercial		-8 (-12 to -5)	-11 (-18 to -7)
	Com. Developed	-11 to -10	-14 to -10
	Com. Developing	-7 to -3	-11 to -10

Figure 4.5. SSP2 results

4.2.6 SSP3 results

The SSP3 scenario - “Regional Rivalry” foresee a low economic development and high levels of inequalities between world regions.

GDP per capita: The SSP3 scenario is, after the SSP4, the scenario with the highest inequalities in GDP cap growth. Differences between developed and developing countries by 2100 are of about 140%. Economic growth is the lowest across the SSPs, even for rich countries. Developing countries do not increase their GDP cap levels above 50’000 dollars/cap while in the SSP1 they are all above that level and in the SSP5 above 100’000 dollars/cap.

Tertiary education levels: The share of population having an high education is the lowest of all SSPs. Developing countries all stay below a threshold of 15% throughout the century, while in the SSP1 they were above 20% by 2100. The SSP3 scenario is also the one showing the highest disparities in education levels between developing and developed countries, with the latter showing constant and slightly decreasing (but higher in absolute value) trends throughout the century.

ETP-WP ratios: Trends for developed countries are mostly the same throughout the SSPs. Instead developing countries in the SSP3 show constant levels from 2060 to the end of the century. Investment in health and education are low and so the demographic transition. WFH potential: It is the lowest across all SSPs, with levels reaching 40% only by the end of the century and only for developed countries. Developing countries show the lowest increases, with a median value of 30% of employed population by 2100.

WFH total population: A share between 7 to 12% of the population is at WFH around 2050. Levels are constant throughout the century. Developed countries show slightly decreasing trends, the opposite occurs for developing regions.

Coefficient of commercial reduction: This scenario sees the second greatest differences between regions after the SSP4. Average WFH subcommercial reductions are of 10% for developing regions by 2050 and of 20% for developed ones.

Final Energy net variations for the Building sector in the SSP3 scenario are almost exactly zero throughout the century. Yet this trend hides strong differences between developing and developed regions. In fact, they are the highest after those found in the SSP4. Developed regions already by 2050 decrease consumptions of 2.5% while developing regions show net increases from 0 to 2%. By 2050 the residential sector should experience an increase of about 3%, while the commercial sector a decrease of around 6%. Trends both for the residential and commercial sectors are expected to remain constant throughout the century. Yet the lower range of commercial reduction reach -18 by 2100.

SSP3 Final Energy variations %			
		2050	**2100**
Net		0 (-0.5 to 1)	0 (-0.5 to 0.5)
	Net Developed	-3 to 2.5	-4 to -3
	Net Developing	0 to 2	0 to 2
Residential		3 (1 to 4.5)	3 (1 to 5)
	Res. Developed	2 to 3.2	2 to 3
	Res. Developing	2 to 3.5	2 to 3.6
Commercial		-7 (-11 to -5)	-6 (-11 to -5)
	Com. Developed	-11 to -8	-11 to -10
	Com. Developing	-6 to -3	-7.5 to -2.5

Figure 4.6. SSP3 results

4.2.7 SSP4 results

The SSP4 scenario - “Inequality” narrative is a one where a gap widens between educated and uneducated population, rich and poor and high tech and low tech regions. Hence, in this scenario are expected the biggest differences in WFH adoption levels.

GDP per capita: This scenario foresees the third highest GDP cap growth for developed countries among SSPs and at the same time the second lowest for developing countries. Half of developing regions does not exceed 50’000 dollars/cap by 2100. Some regions show GDP cap levels of 10’000 dollars/cap by 2100 while others of 125’000.

Tertiary education levels: In the SSP3 the global share of highly educated population is the second lowest after the SSP3. Developing countries show slightly increasing trends throughout the century.

ETP-WP ratios: Developed and developing regions converge toward different levels by 2100. The former around shares of 12% while the latter of 25%. The considerations are the same of the SSP1 and SSP2.

WFH potential: In the SSP4 the greatest regional differences are shown, particularly by the end of the century where the strong GDP growth of developed countries allow them to exceed the 40% threshold of WFH. Some regions never exceed 20% while others reach about 60% by the 2100. By 2050 however, developing countries show on average higher levels of WFH potential than in the SSP3 scenario.

WFH total population: As expected, strong differences emerge by the first half of the century. In developed regions around 12% (from 10 to 15% by 2100) of the population is at WFH while in developing regions shares are from 5 to 10%. By the end of the century yet, the shares tend to converge between regions to values of 10%.

Coefficient of commercial reduction: Developed countries show average WFH subcommercial reductions of 5 to 12% by 2050 while by the end of the century they split up in two groups, one below levels of 15% and another already reaching 20% by the 60s. This is coherent with the SSP4 narrative.

Final Energy net variations for the Building sector in the SSP4 scenario are almost zero throughout the century. Yet, differences between developed and developing regions are great. By 2050 the former group increase net consumptions or slightly reduce them, while the latter on average see reductions of 5%. By 2050 the residential sector experience an increase of about 3%, while the commercial sector a decrease of 8%. Trends both for the residential and commercial sectors are expected to remain constant throughout the century.

4.2.8 SSP5 results

The SSP5 scenario - “Fossil fuel Development” foresee improvements in education and health but at high environmental costs. A constant and rapid economic growth

SSP4 Final Energy variations %			
		2050	2100
Net		0 (-1 to 1)	-1 (-2.5 to 0)
	Net Developed	-3 to -2	-7.5 to -2.5
	Net Developing	-1.25 to 2	-2.5 to 2
Residential		3 (1.25 to 5)	3 (1.25 to 4)
	Res. Developed	2 to 3	2 to 3.5
	Res. Developing	2.5 to 4	2.8 to 3.2
Commercial		-8 (-14 to -5)	-11 (-18 to -7)
	Com. Developed	-11 to -10	-20 to -11
	Com. Developing	-10 to -2.5	-11 to -4

Figure 4.7. SSP4 results

takes place all over the world. This extreme scenario is of particular interest as the new equations implemented in EDGE are tested almost at their limits. As example WFH potential's function rise after a plateau appears clearly for most of the country, while in the previous SSPs it emerged less frequently and only closing to the end of the century.

GDP per capita: In the SSP5 is foreseen the strongest and fastest economic growth and convergence between regions. GDP per capita of the "poorest" region in the SSP4 is eight times higher in the SSP5. Levels of GDP cap reached by developed countries by 2100 in the SSP1 are now reached around the 60s, and those of developing countries around the 70s. The richest and poorest region by 2100 differs by the mean only of 25%.

Tertiary education levels: Along with the SSP1, the SSP5 foresee the highest share of population with a tertiary education level. The trend is almost identical to the SSP1 one. First is experienced a strong rise in the first half of the century, then after the 60s the trends stabilize around values of 25% for developing regions and of 30% for developed ones.

ETP-WP ratios: In the SSP5, similarly to the SSP1, developed and developing regions converge towards similar demographic patterns. Fertility is lower for developing countries, and life expectancies increase. The fraction of population employed is therefore lower than in the SSP2, SSP3 and SSP4, from 10 to 20%.

WFH potential: Developed regions exceed the 40% threshold by far around the mid of the century. By 2100 about 70% of employed population is at WFH in developed countries and around 60% in developing countries. This behavior is highly speculative as was explained in the WFH chapter. The only interpolating point for WFH levels higher of 40% was taken from Liechtenstein. Yet, it was kept to simulate a sort of "highest WFH scenario".

WFH total population: This extreme increase in the WFH potential however, is not reflect in the share of total population, which is overall identical to the SSP1 one, around 10 to 15%. This is due to the counteracting effects of GDP growth (positive) and demographic transition (older population).

Coefficient of commercial reduction: The logistic contribution of the coefficient is showed clearly already from the mid of the century. A strong and fast rise followed by slower growths. In fact the sigmoid midpoint is set to WFH pot. values of 50%. Overall the coefficients takes values from 15 to 20% by 2050 and of about 50% (with a max. of 60%) for developed regions and 40% for developing ones by 2100.

Final Energy net variations for the Building sector in the SSP5 scenario are of about -1% by 2050 and of -5% (-10 to -3) by 2100. In the first half of the century, as in the others SSPs, developed countries exhibit already reductions while developing regions net increases. In the second part of the century instead this scenario differs from the others due to the strong increase in the coefficient of subcommercial reduction. Developed regions by 2100 decrease net consumptions of 15% while developing regions of about 5%. By 2050 the residential sector should experience an increase of about 3.5%, while the commercial sector a decrease of around 10%. After the 60s the reductions in the commercial sector reach a mean of 25% while increases in the residential levels of about 5%.

SSP5 Final Energy variations %			
		2050	**2100**
Net		-1 (-1 to 0)	-5 (-10 to -3)
	Net Developed	-4 to -2	-15 to -8
	Net Developing	-2.5 to 1.25	-7.5 to -2.5
Residential		3.5 (1.5 to 5.3)	5 (1.8 to 7)
	Res. Developed	2 to 3	3 to 5
	Res. Developing	3 to 4	2.5 to 5
Commercial		-10 (-15 to -6)	-25 (-36 to -15)
	Com. Developed	-12 to -11	-31 to -27
	Com. Developing	-10 to -5	-28 to -17

Figure 4.8. SSP5 results

4.2.9 Q and A

Why does WFH show net global zero impacts on Final Energy?

1. Developing regions shares of Residential End Uses “Appliances and Lighting”, “Space Cooling” and “Water Heating” are considerable higher than those of developed countries. In chapter 3 section 2.3 are explained the reasons, mainly correlated to commercial floor area and climatic/economic drivers. (eg. Space Cooling residential share which see a tremendous rise in developing regions). Any delta applied to the residential sector will therefore have a much higher weight on developing countries.

2. The shares of employed population are always higher for developing countries. Those of WFH potential are instead lower due to lower GDP cap levels. The two effects compensate and thus fractions of total population at WFH are similar for developing and developed countries. However, the residential shift depend on the ETP ratio while the commercial one only on the WFH potential, therefore developing countries commercial reductions are always lower while the residential shift is no affected by lower GDP cap thanks to the demographic compensation.

3. The contrary happens to developed countries.

4. The compensation is therefore: *Within countries:* between commercial and residential sector. *Across countries:* between developed and developing regions. Overall effects are therefore globally zero.

What is the explanation for regional differences being so sharp in all scenarios, even in the SSP1 and SSP5?

The GDP per capita dimension, which tends to converge sharply between developing and developed countries in the SSP1 and SSP5 scenarios, drive the overall global "mean" direction toward higher decrease or increase in FE consumptions. Yet, within years differences are effects of drivers which are not dependent on GDP cap, as ETP ratios, climatic drivers and shape of the implemented curves.

4.2.10 End Use, Energy Carriers results

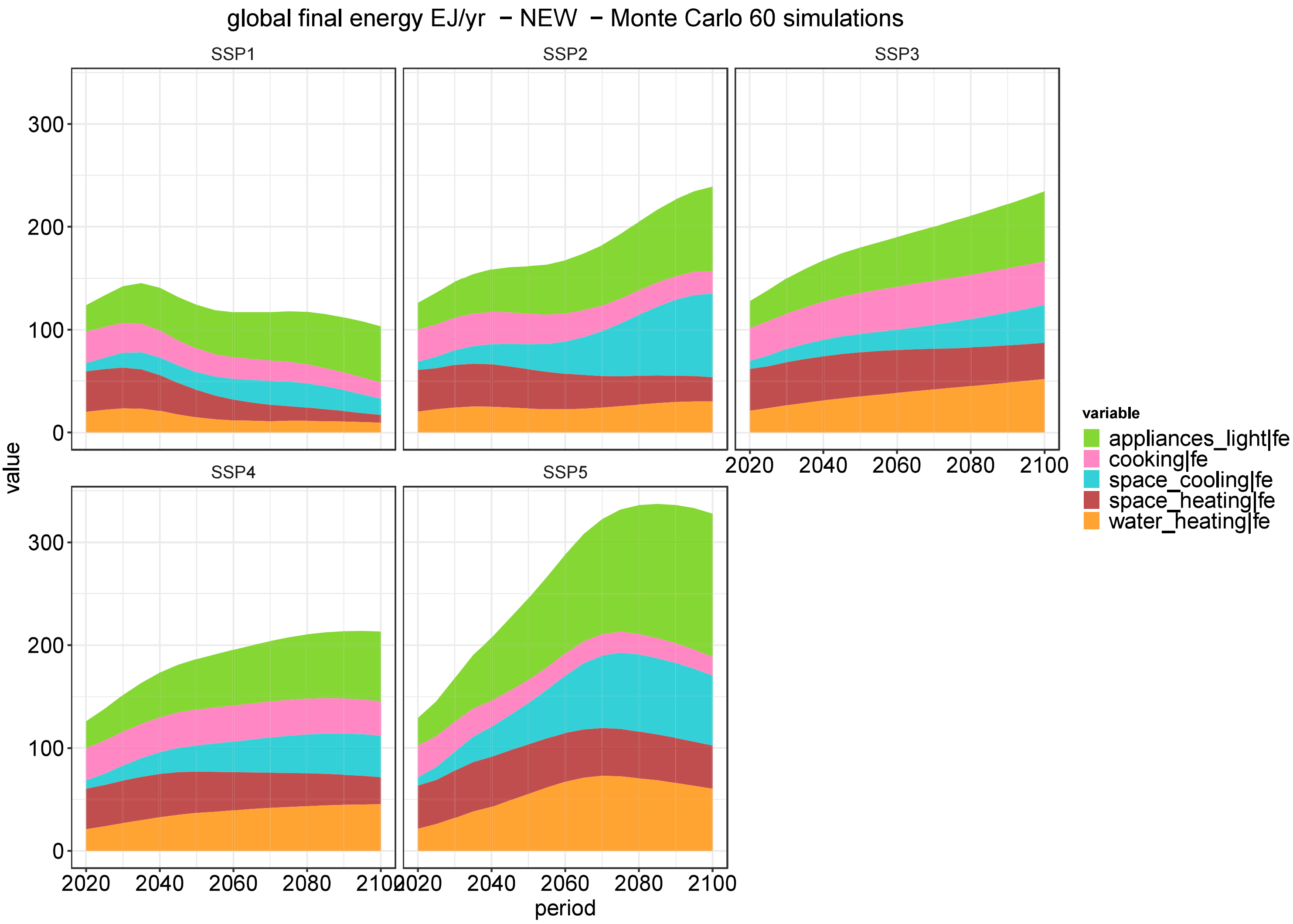
In the next four pages are shown:

1. Global Final Energy (Building sector) in EJ/Yr, this graph is almost identical to the Business as Usual one (No WFH scenario) as the scale of changes is of 2 to 20 EJ/Yr while global FE demands are of about 100 to 300 EJ/Yr. Below are shown instead the deltas grouped by End Use.

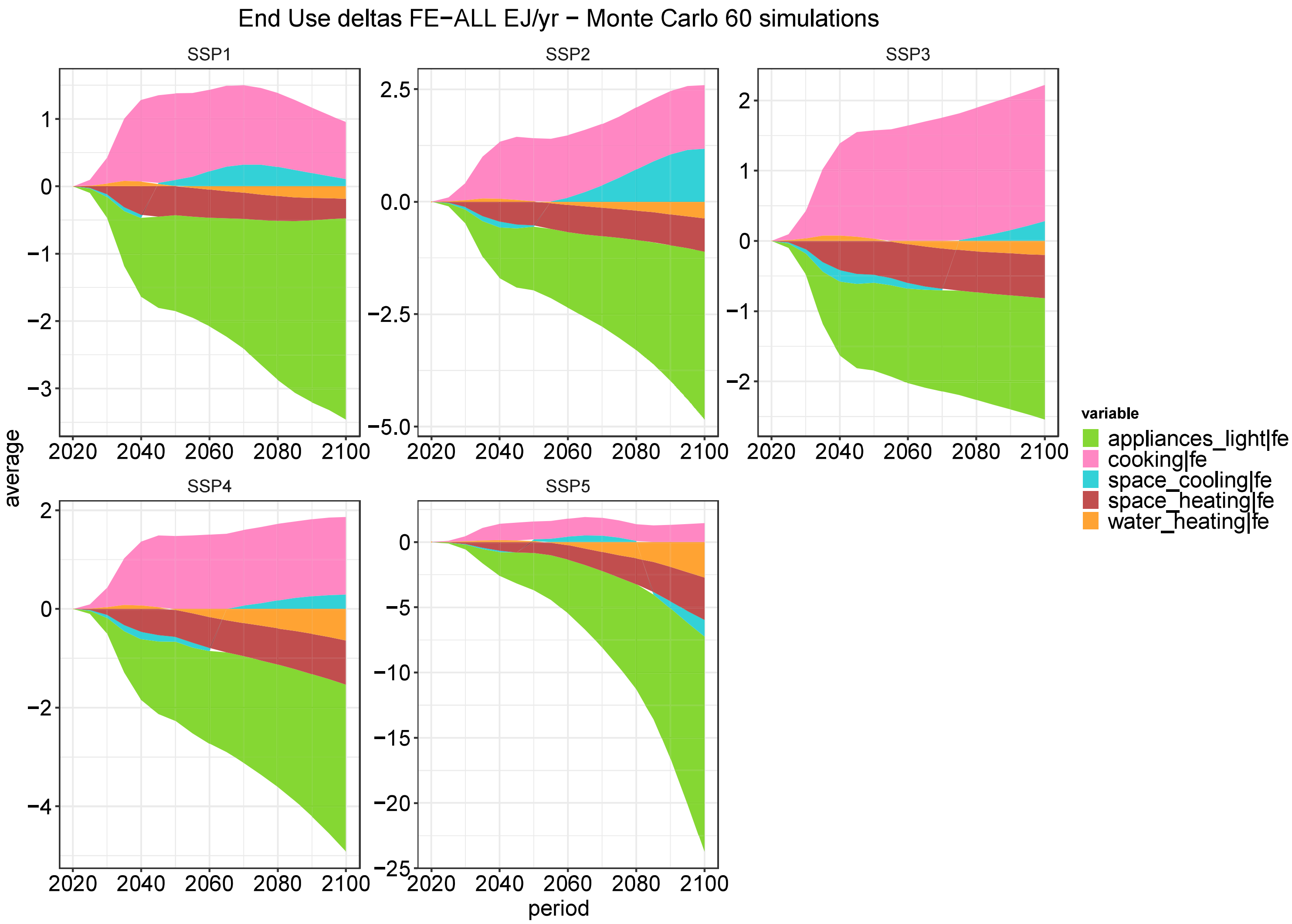
2. Global Final Energy for the Commercial sector with below relative deltas.

3. Global Final Energy for the Residential sector and deltas.

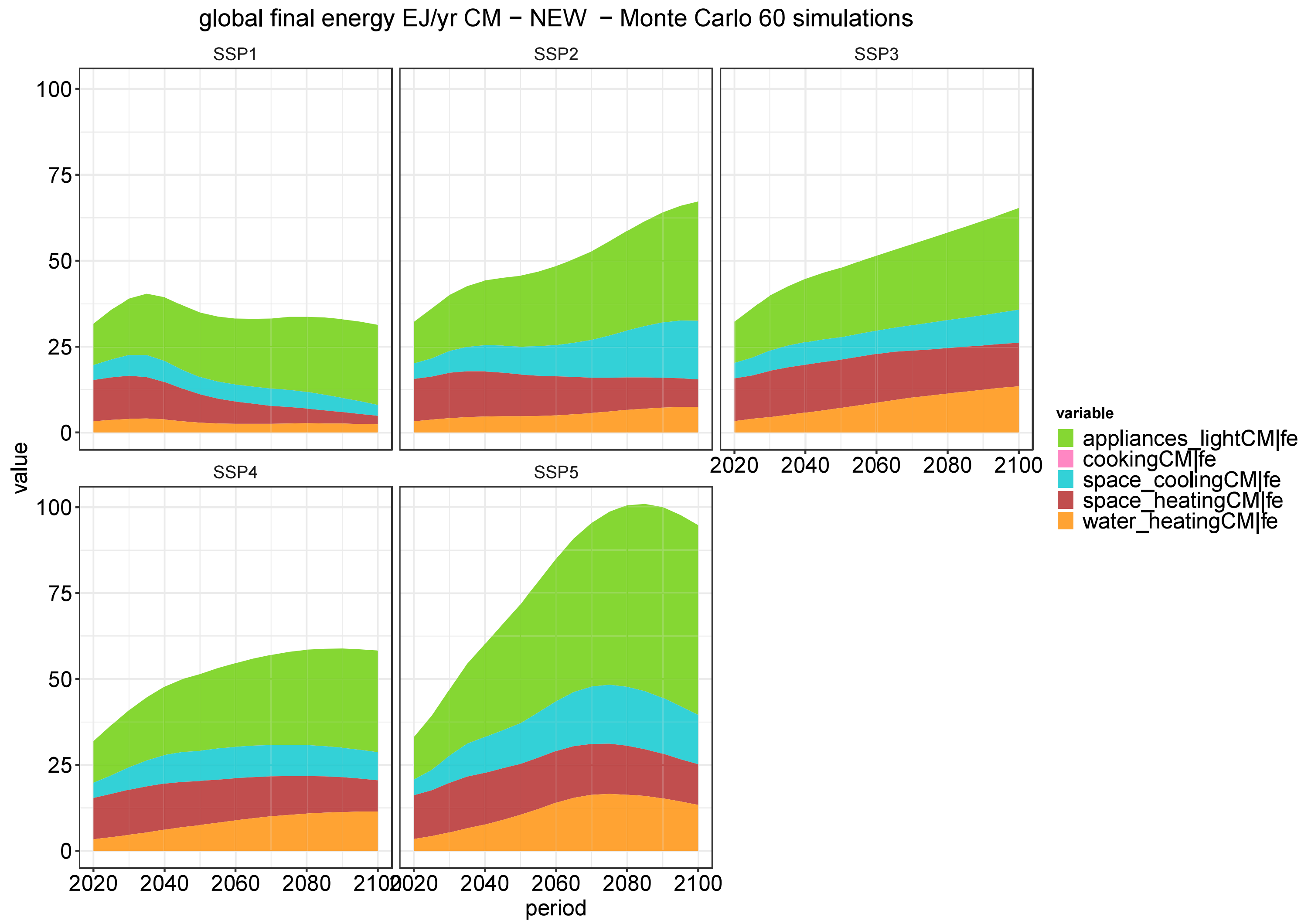
4. Energy Carriers deltas.



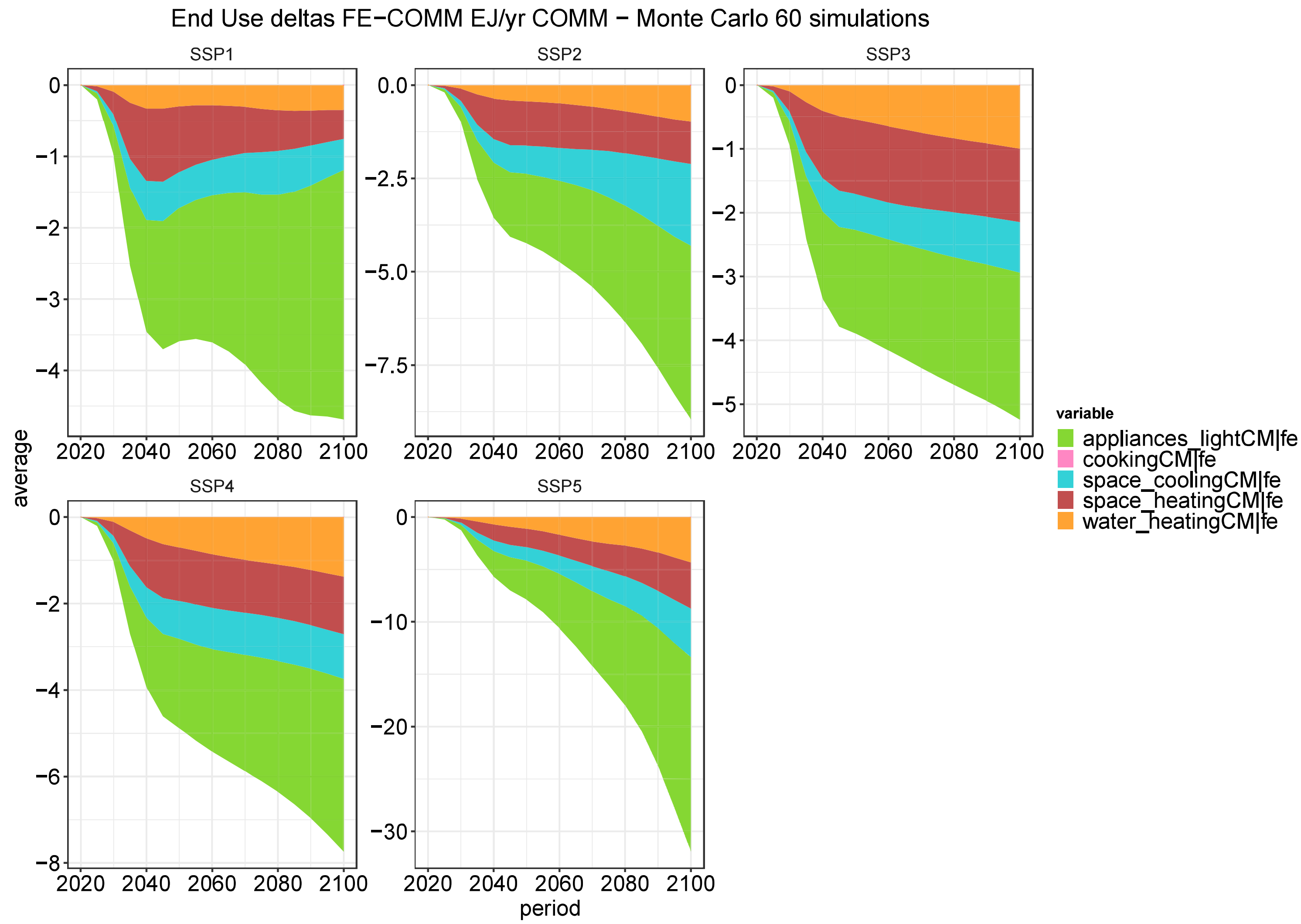
global final energy EJ/yr − NEW − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period
variable
appliances_light|fe
cooking|fe
space_cooling|fe
space_heating|fe
water_heating|fe



End Use deltas FE−ALL EJ/yr − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period
variable
appliances_light|fe
cooking|fe
space_cooling|fe
space_heating|fe
water_heating|fe

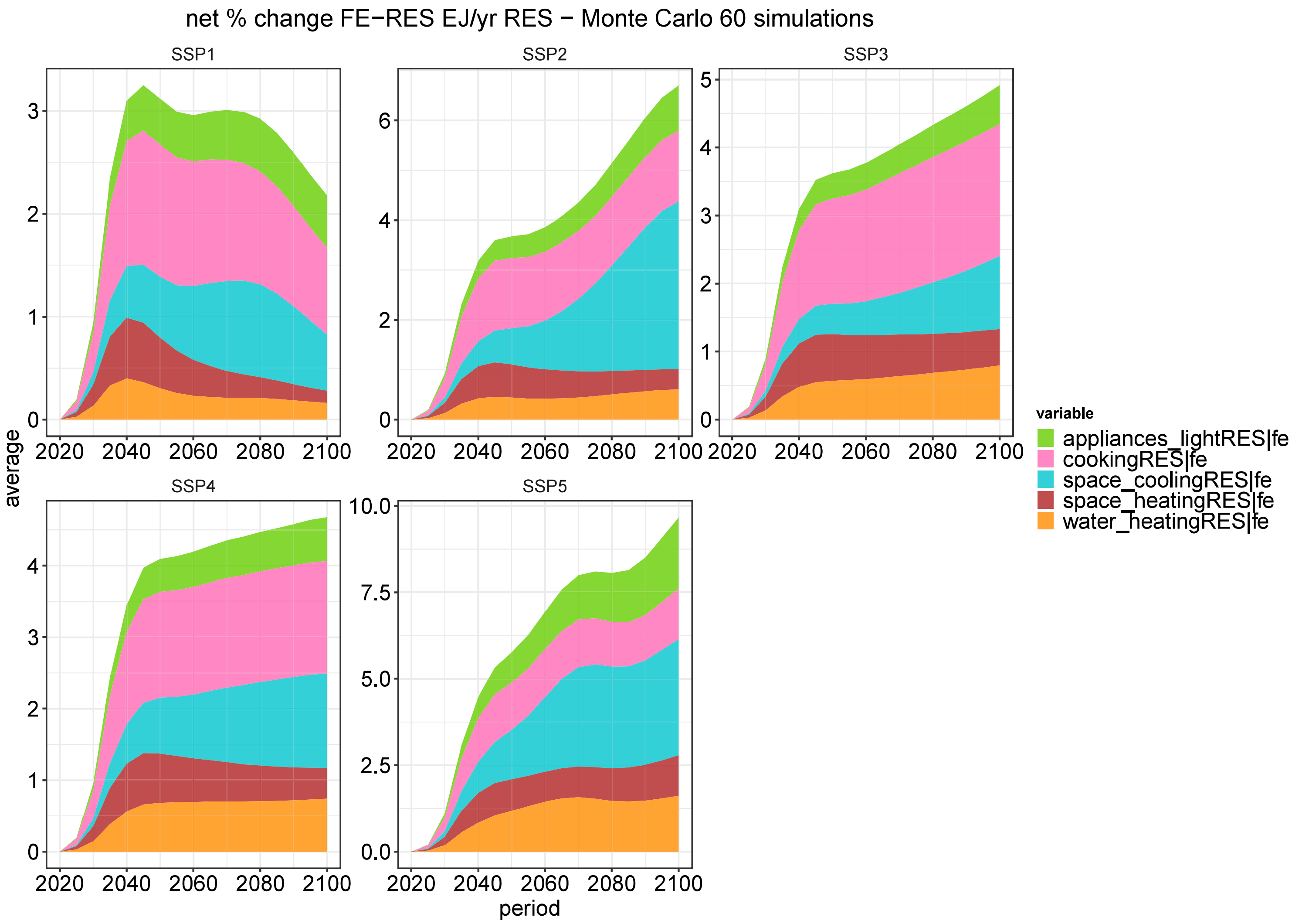


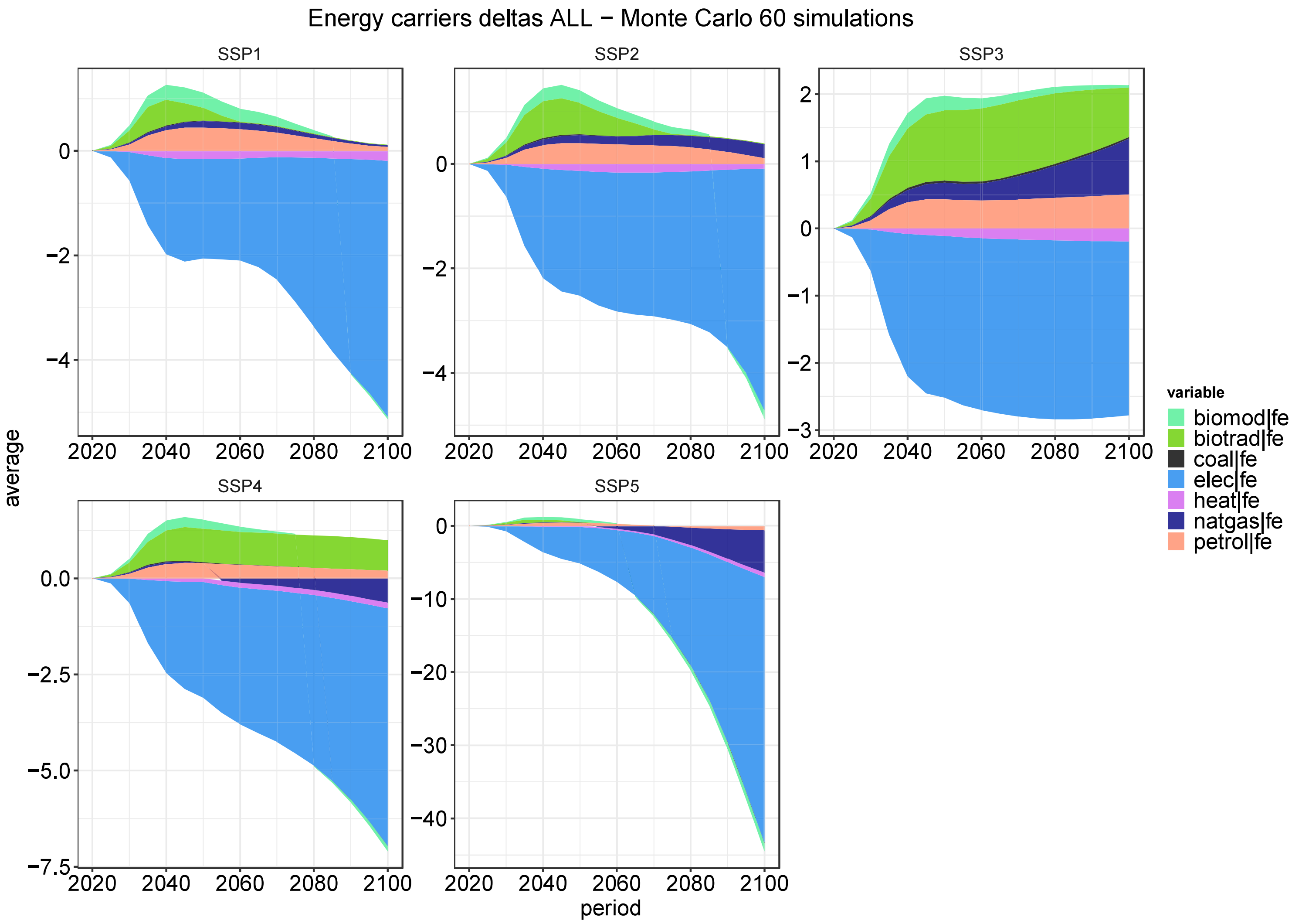
global final energy EJ/yr CM − NEW − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period
variable
appliances_lightCM|fe
cookingCM|fe
space_coolingCM|fe
space_heatingCM|fe
water_heatingCM|fe



End Use deltas FE−COMM EJ/yr COMM − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period
variable
appliances_lightCM|fe
cookingCM|fe
space_coolingCM|fe
space_heatingCM|fe
water_heatingCM|fe


global final energy EJ/yr RES − NEW − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period
variable
appliances_lightRES|fe
cookingRES|fe
space_coolingRES|fe
space_heatingRES|fe
water_heatingRES|fe


net % change FE−RES EJ/yr RES − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period
variable
appliances_lightRES|fe
cookingRES|fe
space_coolingRES|fe
space_heatingRES|fe
water_heatingRES|fe



Energy carriers deltas ALL − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period
variable
biomod|fe
biotrad|fe
coal|fe
elec|fe
heat|fe
natgas|fe
petrol|fe

Global Final Energy

The major trends shown in the Global Final Energy graph are due mainly to the behavior of the default equations implemented in EDGE and presented in chapter 2. The rise of cooling demand is clearly evident in those scenarios that fail to adopt environmental CC policies and thereby to contain temperature increases. Its shares are of about 4% of the 2020 FE demand, while 11 to 37% in 2100. Climate Maximum thus tend to increase, driven by higher values of CDD, especially in mid latitude developing regions. In the energy intensive SSP5 all End Use (except cooking) demands increase in absolute values up to 2080. This is caused by

1. The strong economic growth.
2. Population increment up to the 60s.
3. Climate change induced temperature increases.

Lighting and Appliances tend to increase strongly in all scenarios. From values of about 23 EJ/Yr in 2020 they reach a range of 70 to 200 EJ/Yr in 2100. In global per capita terms this is equivalent to about (rough estimate) five times averages values for 2020. This strong increase is an effect of the absence of saturation (see chapter 2) in the AL demand equation.

The relative share of demand for heat, cooking, space heating and water heating do not show the strong increase of AL and SC, this is due to:

1. Reduced heat demand in particular in mid latitude developing countries due to CC.
2. Improvements in energy efficiency and shifts in regional energy ladder towards more efficient fuels.
3. Saturation in the implemented equations. (Space Cooling was implemented with a saturation effect but the Climate Maximum increase balances it)

Deltas were calculated as the difference between values obtained with the new WFH equations and those resulted from the default settings. Thus trends showed in delta, despite being similar to the one at an aggregated level, are in fact caused exclusively by the new equations. These equations of course have assumptions in commons with the EDGE default ones and so are explained similarities in graph. As example, Cooling demand show a semi logistic increase both in the SSP2 scenario and in the SSP2 delta graph. As is explained later, this is caused by identical assumptions in the Cooling demand EDGE equation and Residential/Commercial shares.

Cooking demand show a net increase due to WFH. This is an effect of the choice of assigning Cooking EU only to the residential sector, according to IEA projections.

Space Cooling instead show negative deltas up to 2040-2060 in most of the scenario (excluded the SSP5) and positive deltas from that period on. This is an effect of the increasing shares of residential Space Cooling for developing regions (up to 80%). They are projected to increase strongly in the first half of the century, to then reach economic and climate saturations. As was explained in the previous section, residential consumption are to increase as an effect of WFH, and particularly in developing countries. SC shares for developed regions are instead much higher in the commercial sector (80%), therefore global SC trends are the results of a compensation effect between strong net increases in developing regions and decreases in developed ones.

Water heating demand show an opposite trend. First it increases in the first half of the century due to its highest residential shares, from 60 to 90% for all regions, then tend to decrease when more efficient reductions in the commercial sector start to take place according to the logistic shape of the coefficient of subcommercial red. Yet, this effect is extremely low and only in the SSP5 it is clearly displayed due to the highest values of WFH potential and thus of commercial reductions.

Space Heating shares for the residential sector are instead high for developed countries, about 75% but very diversified among developing, from near zero to 60%, according to climatic patterns. On average the effects of commercial reductions prevail, and SH consumption decrease due to WFH during the century.

Appliances and Lighting FE show a clear opposite trend to Cooking. It strongly decreases throughout the century. This happens despite developing regions increasing residential AL shares from about 50% in 2020 to 60-70% in 2100. At a global level instead AL shares are constant over the century, as they decrease in favor of the commercial sector in developed countries. But AL demand in developed regions accounts for about 60% of FE in all SSPs but in the SSP3 where it's about 30%. In developing regions instead, they account for 60% of FE only in the SSP1 (convergence between nations). Hence the weight of developed countries for AL is higher and strongly contributes to overall global AL FE reductions.

Energy Carriers

The trends shown in the graphs are originated by the new WFH equations and by EDGE assumptions on Energy Ladders shifts. To explain which kind of dynamics are involved in those energy carriers showing increasing trends, two divergent scenarios are analyzed, the SSP1 and the SSP3. Moreover, the focus is on a developing region, Africa, and on one End Use, cooking. In fact, as is explained in the previous paragraphers, Cooking is the End Use showing greatest increments and this is to occur mostly in developing regions, where residential WFH induced increases weight more on the total demand.

In the picture below are shown the shift in Cooking EC composition both for the SSP1 and the SSP3.

In the SSP1 scenario general improvement in standard of livening, energy intensity and sustainable development lead to a shift of the energy ladder in developing regions

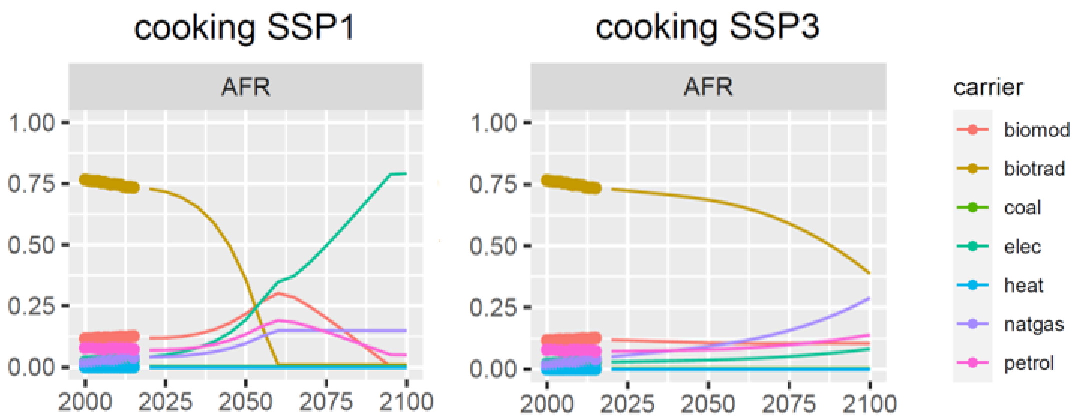


Figure 4.9. Energy Ladder shifts for CK

toward greater shares of electricity. From shares of about 0% in 2020 it constantly increases up to levels of 75% in 2100. Conversely, traditional biomass, which nowadays almost fully provides in Africa the energy needed for cooking, decrease constantly from levels of 75% to zero around the mid of the century. Petrol and "improved" biomass increase their share up to 25% by the 50s to then decline to zero by 2100. Natural Gas slowly increases its shares in the first half of the century and then substitutes the shares of Petrol and improved biomass. This behavior is reflected in the SSP1 graph for delta. It is in fact observed an initial increase in traditional biomass (due mostly to the WFH induced increments in cooking in developing regions) that is then substituted by petrol. Natural gas and electricity cooking-increments are not shown as they also increase in the commercial sector and are hence "hidden" by their respective strong decrease.

In the SSP3 scenario instead electricity is not used in developing regions as EC for cooking. (extremely low increase). Most of FE is provided by 2050 still by traditional biomass (70%) and by an heterogeneous mix of petrol, traditional biomass and natural gas. However by the end of the century the decrease of traditional biomass becomes more pronounced and natural gas "take-off" and substitute progressively its share. By 2100 traditional biomass accounts for around 40% of cooking FE and natural gas about 25%. The rest is provided mostly by petrol (17%) and traditional biomass. This trend is clearly shown in the SSP3 delta graph. First the WFH induced increase in cooking EU is fueled by traditional biomass, later in the century natural gas increases its contribution followed by petrol, which shares remain constant throughout the century, as is also evidenced in the Energy Ladder graph.

The strong decrease in electricity EC has a straightforward explanation and is mostly explained by:

1. High shares of commercial AL in developed countries. (60% constant throughout the century). Also, Space Cooling commercial shares are high with levels of about 75%. SC in developed countries is mostly provided by electricity (around 90% constantly through the century for USA).

2. AL accounts for around 50% of building FE demand in developed regions (2100,

rough mean between SSPs). SC much less (5 to 10%) but HVAC systems in the commercial sector are the principal singular type of consumer.

3. Global Final Energy for the Residential sector and deltas.

4. Developed regions experience the strongest decrease in commercial reduction.

4.2.11 Results with DN-World Bank method(2)

Method 2 has been introduced in chapter 3. It is an experimental method that involves the use of both Dingel Neiman interpolation and World Bank "within countries" coefficients. Purpose of this method was adding a deeper demographic component to the projection of WFH potential by linking it to "gender", "education" and "age". A total of 20 country-region specific coefficients were deployed. However some countries like China did not find a match in the World Bank dataset and were thus not modified.

WFH potential obtained with this method is almost reduced to an half with respect to the one obtained with method 1. (From 40 with method 1 to levels of 20%). This happens as the shares of population with a non-tertiary education are strongly penalized. Yet they represent most of the population. Developed countries still show higher levels of WFH potential but contrary to developing regions that increase their WFH, even if by little, they show constant trends throughout the century excluded the outlier SSP5 scenario. This behavior is so explained:

1. The shares of population with a non-tertiary education are higher.

2. Developed and developing regions show in all scenarios apart from the SSP3 and SSP4 similar trends and levels of tertiary education (% of total population).

3. The population of developed countries is getting older in most of the scenario a part from the SSP5, also the one of developing countries, but at lower levels and mostly in the SSP1 and SSP5 scenarios. Older shares of population are penalized in WFH probability.

4. Therefore, the penalizing effects of an older population and of a majority having non-tertiary education (around 70% in most of the SSPs) win the positive contribution of the GDP growth, especially in developed countries. In the SSP5 scenario instead the GDP cap growth is strong enough to raise WFH potential levels towards the ones of method 1, but only near the end of the century.

The impacts on global Final Energy nets are not significant, with respect to method 1. Some differences can be observed in the Residential increases of consumption. Developed regions ones are almost an half (about 1.5%) of those of developing regions (about 2 to 3%). This happens because the lower values of ETP-WP ratios of developed regions are not balanced anymore by higher value of WFH potential. (see previous paragraphers for explanations).

4.3 Reliability of results

4.3.1 COVID 19 Simulation

In order to assert whether the model implemented can adequately reproduces the dynamics involved in a WFH scenario, inputs parameters were modified basing on available literature.

Residential deltas were kept unaltered. The coefficients WFHpot-ETP-WP ratio instead were artificially corrected to simulate the number of people staying at home due to confinement measures. At its peak around 50% of world population was under SIP orders. The coefficient for subcommercial reduction was set equal to the one found for COVID19 (linear savings trend, N equal 1). WFH subcommercial coefficient was set to an higher value of 0.7, with the same standard deviation. This value was inferred from literature. At their peak, lockdown measures involved about 70% of world's total emissions. It was therefore assumed that the share of commercial sector forced to full or partial closures could have been of about 70%.

Results are shown in the next picture and show increases in residential consumptions of about 10 to 15%, decreases in commercial sectors of about 15 to 25% and net variations of 0 to 5% for the building sector.

These results are in line with those obtained by other studies published in 2020 on Nature Climate Change (Le Quéré et al. and M.Forster et al.) In particular residential variations are in line with the average increments of 10 to 20% calculated by the others studies. By changing the subcommercial coefficient of separation to a value of 0.9 the reductions for the commercial sector result from 20 to 30%.

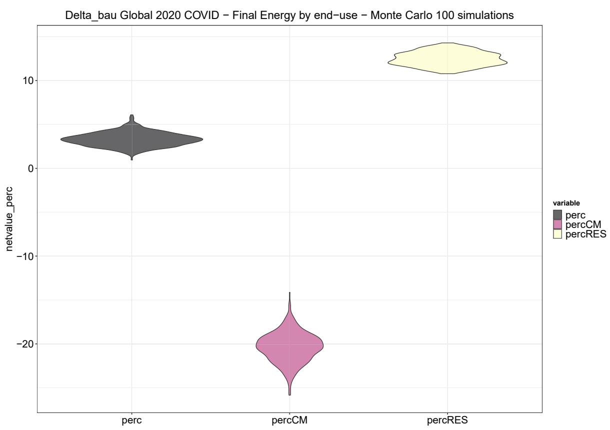


Figure 4.10. Simulation for COVID19

4.3.2 Similar studies

Here is provided a list of studies collected from literature and summarized their findings. All these studies modeled both the residential and commercial sectors, some of them included the transport sector on the overall balance. Some refer to total national consumptions while other to the building sector. However, they all point to the same conclusions, WFH does not seem to affect greatly net energy consumptions due to the balancing effects of residential and commercial sectors.

Table 4.2. WFH-energy studies and results

Reference	**Impact**	**Country**	**Findings**	**Net**
M.Fu et al. [111] 2012	Reduce	Ireland	If 5% of the irish population teleworked full time, final energy consumption would fall by 0.14%.	-0.14%
H.Matthews and E.Williams [112] 2005	Neutral	Usa, Japan	For 2005 estimated teleworking populations and practices in the US (0.4% of total worker days, once a week) and Japan (2.5 million workers, once a week), national level of energy savings is of 0.01-0.4% in the US and 0.03-0.36% in Japan. If 50% of information workers telework 4 days per week, US and Japan national energy savings are estimated at about 1% in both cases.	-1.2%
D.Röder and K.Nagel [113] 2014	Neutral	Germany	WFH of 10% of the sampled population reduces commuter mileage and transport energy consumption of 10% but increases energy consumed at home of the same amount. Office energy consumption is barely affected.	0%
K.Roth et al. [114] 2007	Reduce	US	WFH in US by 3% of the total workforce one or more days per week could reduce annual primary energy consumption by between 0.13% to 0.18% and CO2 emissions by 0.16% to 0.23%.	-0.13%
Y.Shimoda et al. [115] 2007	Reduce	Japan	If the area of used office buildings decreases proportionally to WFH, levels of 60% lead to energy consumption decreases of 0.6% of building total energy consumption.	-0.6%
E.Williams [116] 2003	Reduce	Japan	WFH of 4 days per week by 37% of the total workforce reduces national energy consumption of 2.2%.	-2%

Conclusions

4.4 Conclusions

The main research question this work was intended to answer was whether Work From Home could be a valid option for policymakers to reduce Building sector energy consumptions in the next decades.

Findings show that at "regional" level answers cannot be given disregarding climatic patterns and general economic frameworks of the analyzed country. At a global level instead results from this research confirm the evidence of previous studies of almost net zero impacts of WFH on the Building sector. Yet, this research offers new insights on the dynamics contributing to zero net energy savings. The balancing effect between commercial and residential sectors was widely expected, instead the one between developing and developed regions was less predictable.

Developing regions are expected to experience a strong rise in residential cooling demand, due to improvements in income per capita, but also to Climate Change induced increase in temperatures at mid latitudes. This strong increase is particularly evident in the first half of the century, and the projected increase in commercial floor demand is still not sufficient to balance it. Also, despite WFH potential being lower for developing regions, their share of WFH on total population are higher, due to higher ETP-WP ratios. This happens as their populations are younger and so the shares of people aged 16 to 64. Hence commercial energy reductions for developing regions are lower (being dependent on the unoccupancy levels of work places) while residential reductions depend on the WFH-total population and are therefore unaffected by the lower WFH potentials.

These effects contribute to higher overall residential increases and lower commercial reductions in developing regions, while the contrary happens in developed ones.

An increase in Cooking End Use of about 50% per Home Worker contributes along with Space Cooling to the residential increase both in developing and developed regions. At an energy carrier level, this implies greater consumptions of biomass and oil in the formers and of natural gas in the latter. Also, as improvements in the energy ladder take place in Africa, India etc. Cooking natural gas and electricity gradually substitutes inefficient EC.

This research did not include considerations on avoided commuting due to WFH.

Yet, the conveniency of the adoption of WFH largely depends on energy savings in the transportation sector, as most of the studies suggest. Also, developing regions may result from this research less benefited from WFH, at least in the short term and with a focus on the Building sector. However, road congestion issues in countries like India are major problems that strongly affect business and life quality. The adoption of WFH has therefore the potential to impact greatly, and in a positive way, in sectors not considered by this research.

The adoption of more efficient appliances in the residential sector due to WFH is also a possibility. As some studies indicate, residents give more importance to gas and electricity bills reductions when they start to work from home. Higher interests in the installation of solar panels and renewables were also registered by a research.

On the contrary, rebound effects such higher use of appliances not directly related to WFH or increased miles per worker a day due the moving of WFH workers outside cities were registered by other studies. Also, telework facilities are becoming an option, for those workers who still feel the need for social interactions.

The results of this research on the Building Sector, and the considerations above, seem to suggest that overall *global* strong improvements in energy savings are difficult to reach by adopting WFH. Many counteracting forces are in place within countries (between residential and commercial sectors) and across regions. Also, several cascade effects (increased residential floor area per capita, telework facilities etc) tend to null each other and the overall contribution. At a regional level, developed regions may achieve net savings (in the Building sector) of about 1 to 5% over the century, while developing regions changes from -2 to +2%, according to the SSP scenario. The (extreme) SSP5 scenario is the most optimistic one, and foresee net savings in the Building sector due to WFH of about 5% by 2100 for developing regions, and of 10% for developed ones.

4.5 Future work

Here are summarized the main improvements that could be made in the future on this novel WFH-EDGE model. Some of them have already been discussed in the document.

- **WFH Drivers:** The second method developed to project WFH shares in the future was an initial attempt to incorporate a variety of drivers in addition to the principal, GDP per capita. However, the binding of both Dingel Neiman and World Bank methods into a unique model requires more calibrations to provide greater levels of reliability for the results. In particular, the PIAAC, STEP and LMPS dataset do not cover all EDGE regions, also the standard deviations coefficients introduced in method 2 are referred to the respective country-group survey's averages, which were not calculated in EDGE. Such average, if added, should include an additional GDP cap dimension (and thus temporal one) to allow for its integration in the Dingel Neiman WFH-GDP interpolation.

- **WFH-Productivity:** Some researches have identified positive impacts of WFH on productivity, [117] others instead highlighted negative impacts due to increases in workload and technical issues. [118, 119] Moreover, many of the reports signaling increased productivity levels for WFH workers were produced early in the pandemic, when the sudden shifts in the nature and location of jobs may have "boosted" performances. [120] These variations on productivity could impact on national GDP and hence on GDP per capita, which determine itself WFH levels in this model. A recursive relation could thus be implemented. Yet this improvement would require extent corrections in EDGE, as the algorithm was built to follow a linear computational flow.

- **Price Elasticities:** In EDGE is not implemented any price responsiveness. During the COVID19 pandemic electricity demand fluctuations caused noticeable variations in elec. and gas prices. [121] Most of changes in demand were caused by reductions in the industry sector, but also the commercial and residential sectors played a minor role. The behavior of clients at WFH could have been affected by price reductions, and these dynamics should be included in future models. Moreover, as was mentioned in chapter 3, higher interest of WFH workers for energy independency and self-generation mainly through solar panels or other renewable sources could also affect energy prices. [96]

- **En. Increases:** Residential energy variations due to WFH could be modeled according to projections for floor space per capita, worker's behavioral changes etc. Literature is scarce and attention should be given to cultural variables. [36]

- **RES-COMM Separator:** The commercial-residential separation could be endogenized in EDGE by developing a more complex set of End Use generating equations. They should be split in two distinct blocks, linked each other, one for the residential and another for the commercial sector. As was discussed in chapter 3, for example Cooling EU demand for the res. and comm. sectors behave differently. In such a way it could also be added a recursive relationship between WFH, commercial floor space and FED.

- **WFH-Floor Space:** Residential floor space per capita may depend on WFH. [9] As it becomes structural people may move outside cities, investing in bigger houses and possibly increasing energy consumption per capita. Also commercial floor space may depend on WFH, in complex ways. It could well decrease due to WFH and unoccupancy of offices etc. However the exact dynamics are unclear, due to phenomena like coworking that instead balance floor space reductions. These linkages between floor space and WFH could be inserted in future models.

- **En. Decreases:** The curves of subcommercial reductions were calibrated making assumptions valid for multiple sub commercial sectors, like “Offices”, “Public Sector” etc. Ideally, if in the future more data will be available, specific curves could be modeled, increasing overall levels of detail.

Appendix A

Emissions in EDGE

This section was included in the Appendix as it constitutes a first *exmperimental* attempt to include emissions in EDGE.

EDGE was not equipped with the tools required to calculate variations in emissions due to WFH. In fact, EDGE only provided equations to obtain energy information. However, IEA ETP2017 database, which was exploited previously for the separation of commercial and residential shares, also contains data for emissions in the building sector up to 2060. Results are shown only to 2050. Data are available per end-use and at an IEA regional level. The sequence of steps implemented to allow an integration in EDGE was therefore the following:

1. Calculate the energy intensities per end-use projected in the IEA RTS scenario. Obtained coefficients are in MtCO2/PJ.
2. Merge IEA and EDGE regions and multiply energy variations due to WFH with energy intensity coefficients.

This method requires more developing and ideally it should be favored an approach fully integrating EDGE energy efficiency indicators with emission intensities coefficients. However, given the broad reliance of EDGE on IEA technological assumptions (eg. floor space, efficiency coefficients, residential commercial separation), as first try it can be accepted.

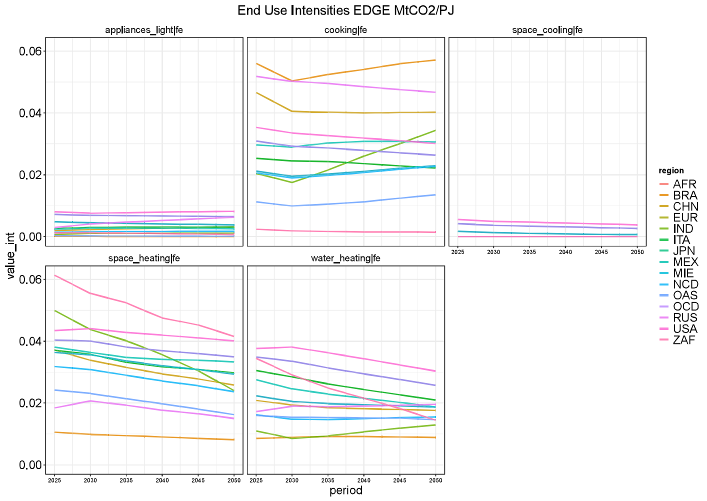
Emissions intensities are projected to decrease for all End Use a part from Appliances and Lighting, which coefficients stay stable up to 2050. Also Cooking EU's coefficients are projected to remain stable, with some regions showing instead increments, as is the case for India and Brazil. AL and SC have very low energy intensities, this happens as they are most linked to Electricity EC. IEA does not consider Electricity embodied emissions, as they are accounted to the Power Sector.

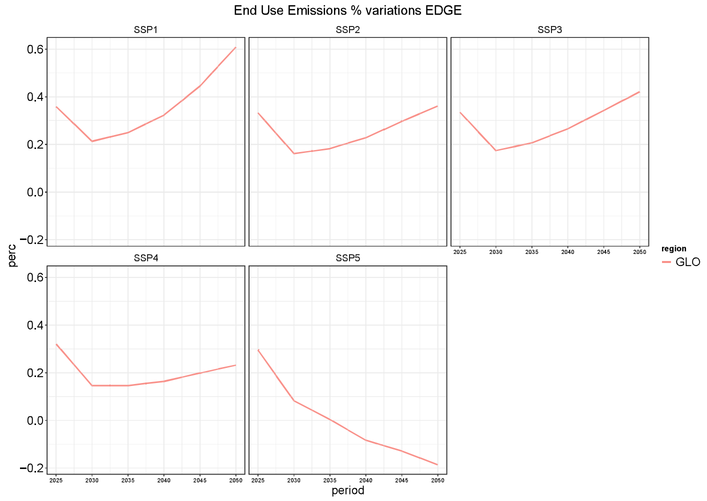
Overall emission End Use intensities are higher for developed countries, according to the IEA RTS scenario. Overall SSPs emissions for the Building sector are lowest for the SSP1 ("Sustainability") scenario, with a strong decrease in the first half of the century from about 3000 Mt CO2 to less than 2000 in 2050. They gradually increase in the SSP2, SSP3, SSP4 scenario. In the SSP3 and SSP4 scenarios the emissions are almost stable. In the SSP5 scenario ("Fossil fuel Development") they reach about 3500 Mt in 2050.

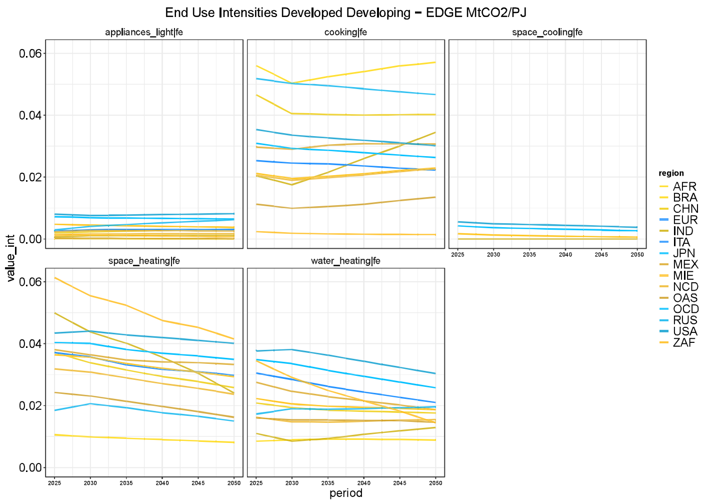
Global variations in emissions seem to suggest small increments, between 0 and 0.6% in all SSP scenarios. Only in the SSP5 the contributions are slightly negative. This happens as Cooking EU FED is projected to increase in all SSP due to WFH. But Cooking is more carbon intensive, according to IEA projections, than other End Uses. Thus, even if at an energy level net variations are slightly negative, resulting net emissions variations result to be slightly positive due to a shift in the EC shares (on the total FC). In the SSP5, as was explained in the "Result" section, the strong economic growth leads to strong WFH commercial reductions and thus overall emissions variations result negative.

These results seem to confirm the findings of the research: WFH is expected to impact almost zero on energy savings in the first half of the century. Moreover, emissions could even increase, due to shifts in the EC mix.

(The results shown graphically in the next pages are obtained from a Monte Carlo simulation obtained from 60 iterations, uncertainties are not shown but of the same magnitude of those obtained for net energy variations' values)


End Use Intensities EDGE MtCO2/PJ
appliances_light|fe
cooking|fe
space_cooling|fe
space_heating|fe
water_heating|fe
value_int
period
region
AFR
BRA
CHN
EUR
IND
ITA
JPN
MEX
MIE
NCD
OAS
OCD
RUS
USA
ZAF


End Use Emissions % variations EDGE
SSP1
SSP2
SSP3
SSP4
SSP5
perc
period
region
GLO


End Use Intensities Developed Developing – EDGE MtCO2/PJ
appliances_light|fe
cooking|fe
space_cooling|fe
space_heating|fe
water_heating|fe
value_int
period
region
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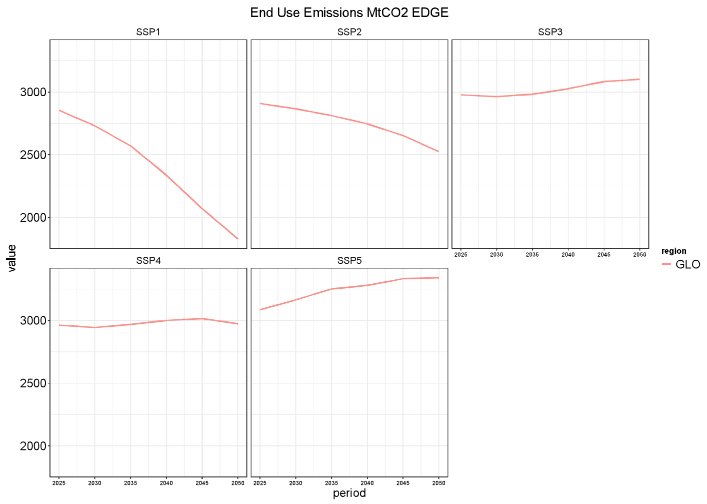
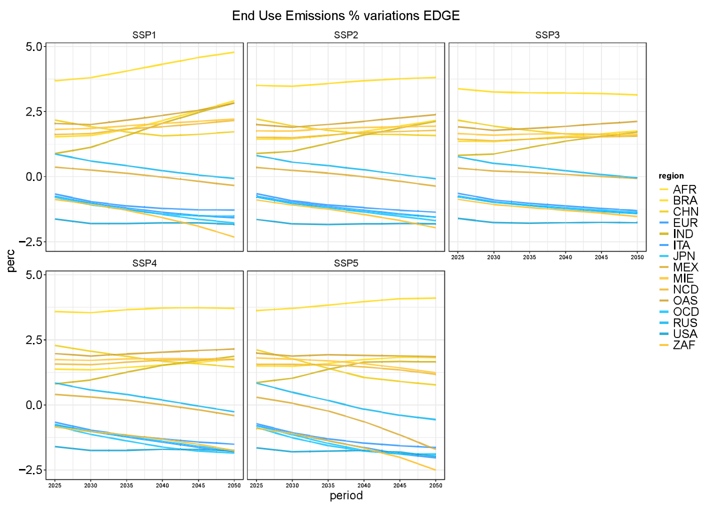
OCD
RUS
USA
ZAF


End Use Emissions MtCO2 EDGE
SSP1
SSP2
SSP3
SSP4
SSP5
value
period
region
GLO

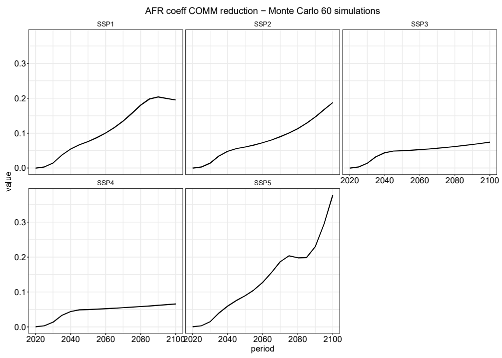

End Use Emissions % variations EDGE
SSP1
SSP2
SSP3
SSP4
SSP5
perc
period
region
AFR
BRA
CHN
EUR
IND
ITA
JPN
MEX
MIE
NCD
OAS
OCD
RUS
USA
ZAF

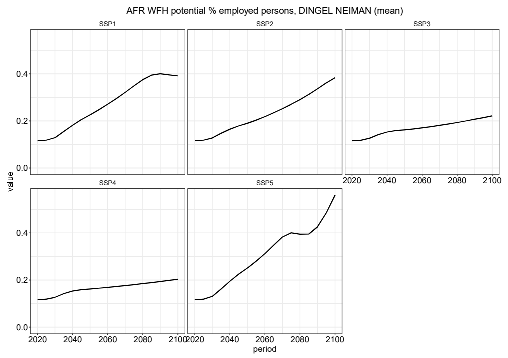
Appendix B

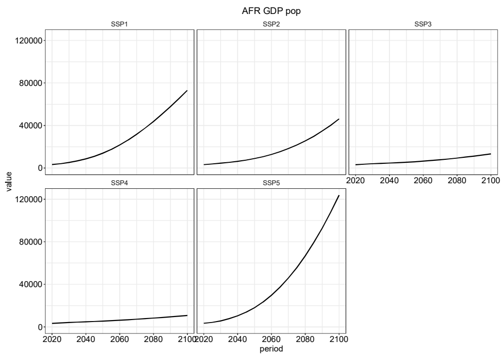
Regions Detailed

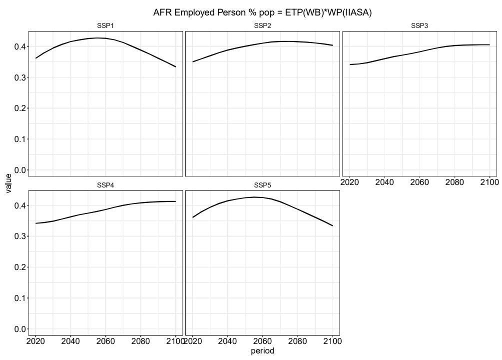
Here are presented results for all of EDGE regions plus Italy. The order is alphabetical:

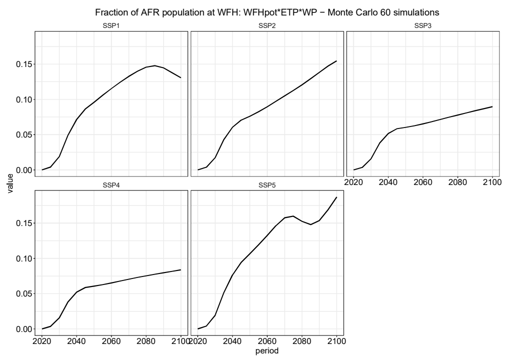
1. AFR Africa
2. BRA Brazil
3. CHN China
4. EUR European Union
5. IND India
6. ITA Italy
7. JPN Japan
8. MEX Mexico
9. NCD Other Non OECD
10. OAS Other South and Asia
11. OCD Other OECD
12. RUS Russia
13. USA United States
14. ZAF South Africa

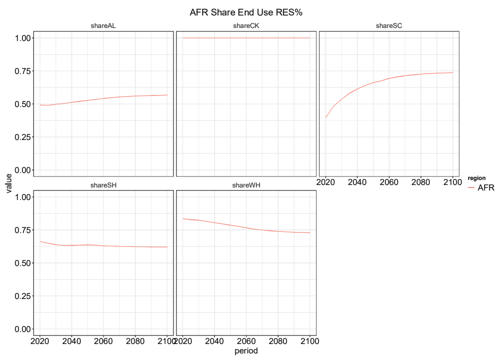

AFR coeff COMM reduction − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

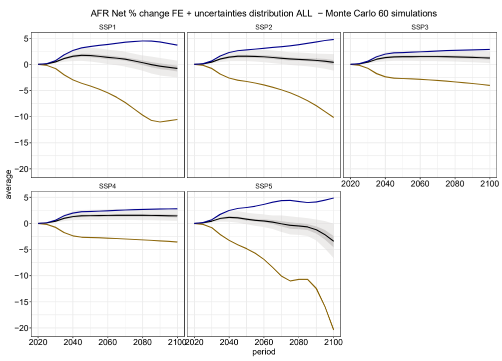

AFR WFH potential % employed persons, DINGEL NEIMAN (mean)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

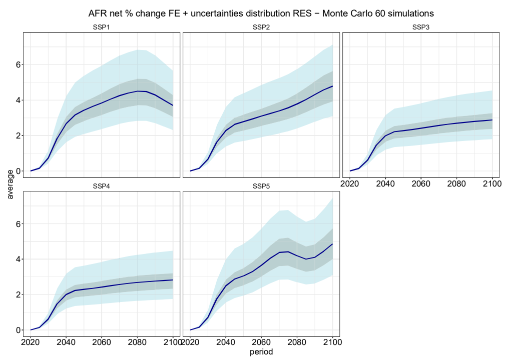

AFR GDP pop
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

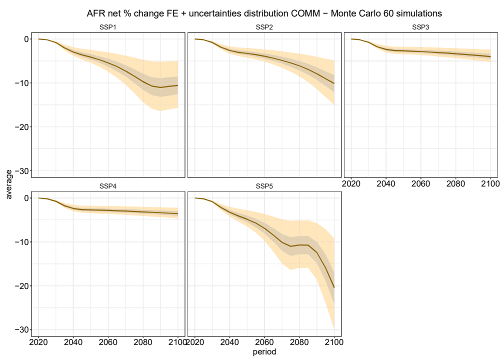

AFR Employed Person % pop = ETP(WB)*WP(IIASA)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

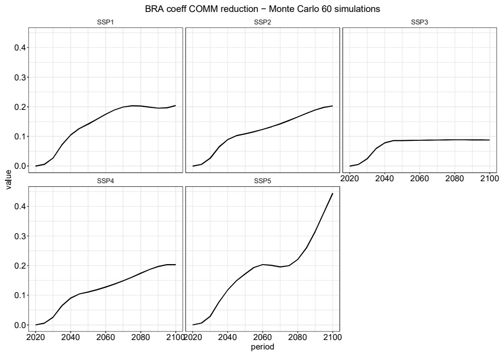

Fraction of AFR population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

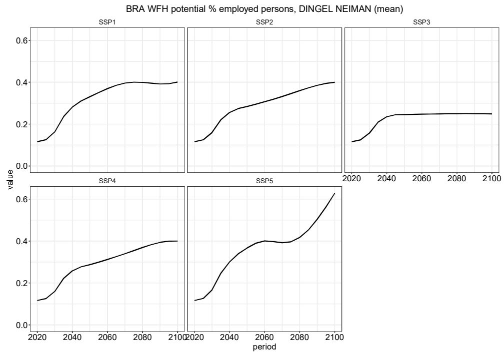

AFR Share End Use RES%
shareAL
shareCK
shareSC
shareSH
shareWH
region
AFR
value
period

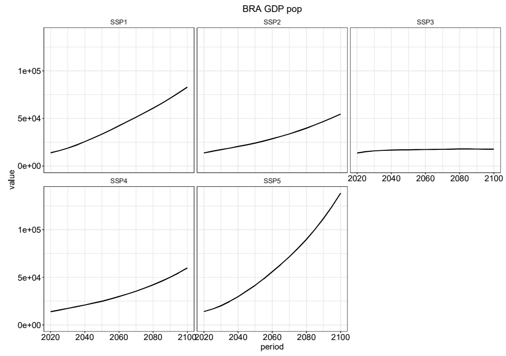

AFR Net % change FE + uncertainties distribution ALL − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

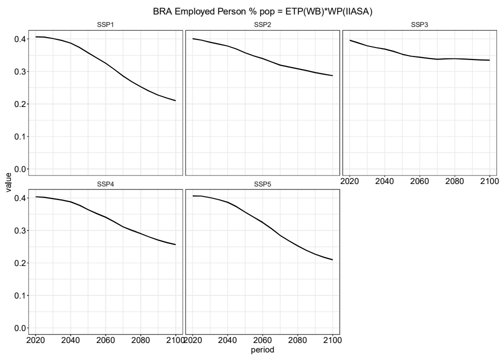

AFR net % change FE + uncertainties distribution RES − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

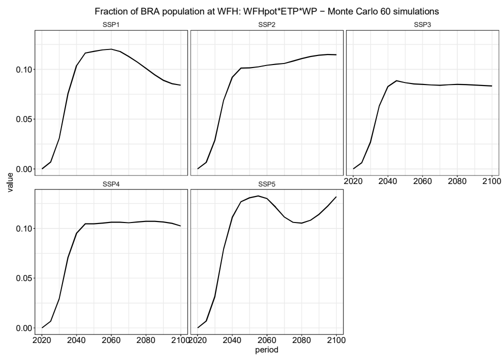

AFR net % change FE + uncertainties distribution COMM − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

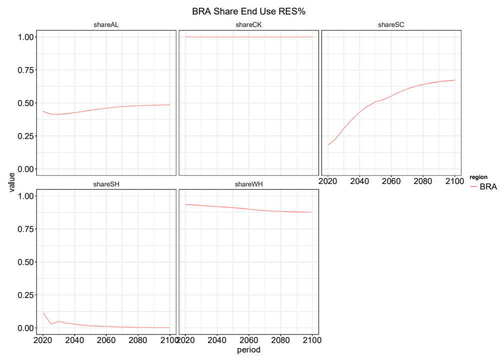

BRA coeff COMM reduction − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

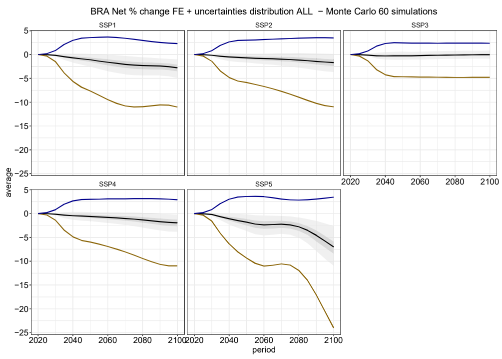

BRA WFH potential % employed persons, DINGEL NEIMAN (mean)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

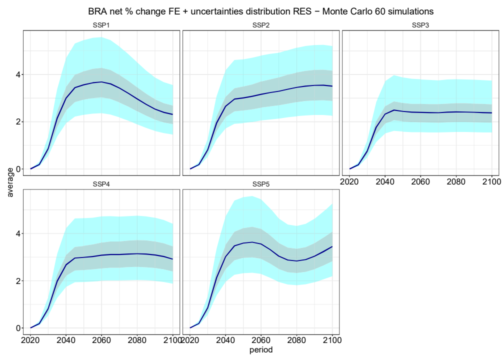

BRA GDP pop
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

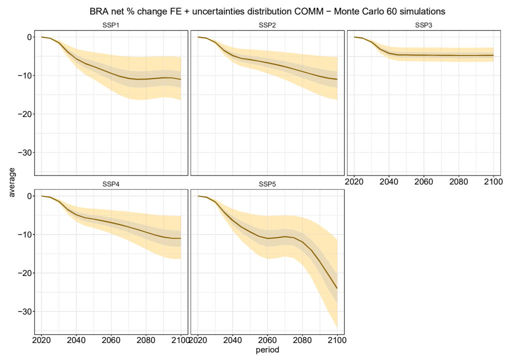

BRA Employed Person % pop = ETP(WB)*WP(IIASA)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

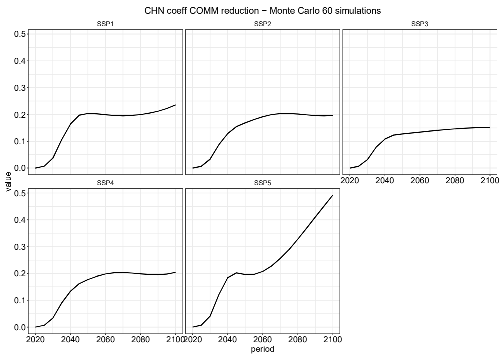

Fraction of BRA population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

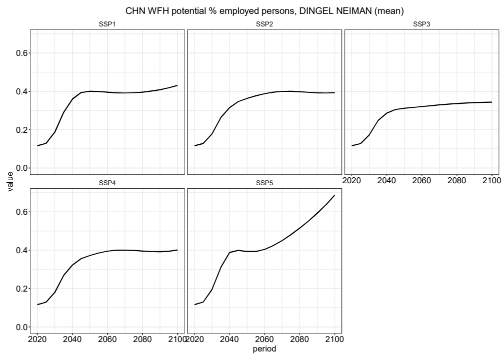

BRA Share End Use RES%
shareAL
shareCK
shareSC
shareSH
shareWH
region
BRA
value
period

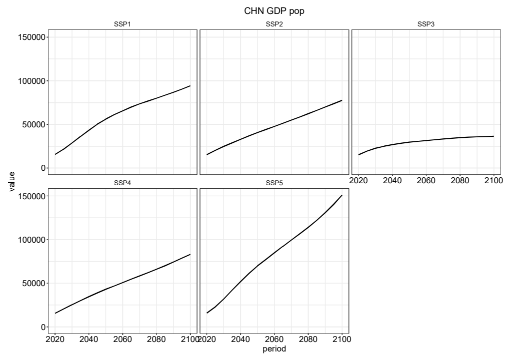

BRA Net % change FE + uncertainties distribution ALL − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

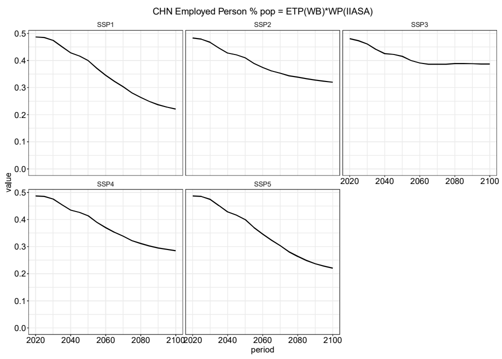

BRA net % change FE + uncertainties distribution RES − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

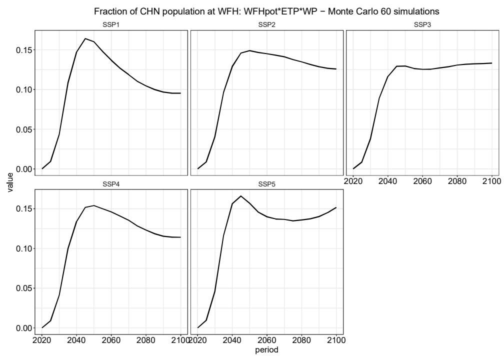

BRA net % change FE + uncertainties distribution COMM − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

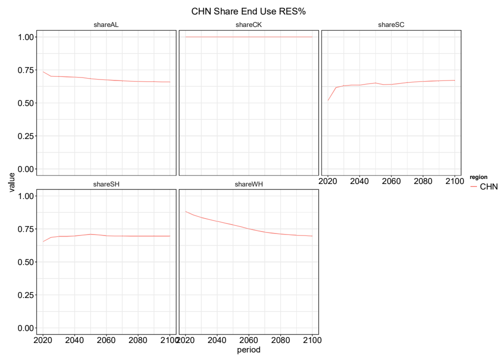

CHN coeff COMM reduction − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

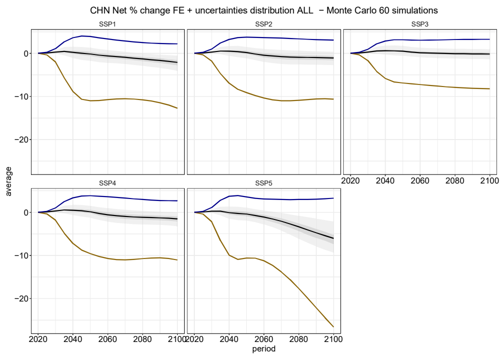

CHN WFH potential % employed persons, DINGEL NEIMAN (mean)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

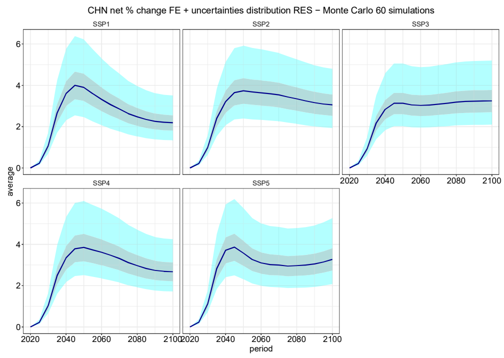

CHN GDP pop
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

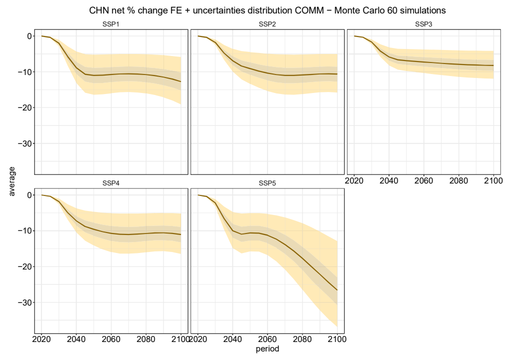

CHN Employed Person % pop = ETP(WB)*WP(IIASA)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

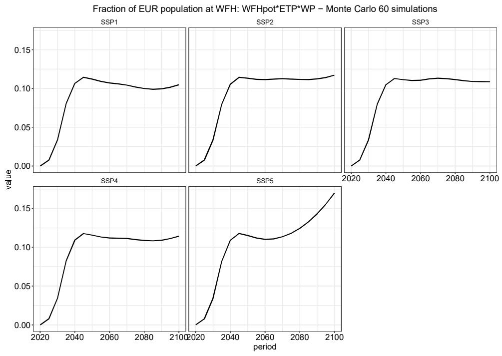

Fraction of CHN population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

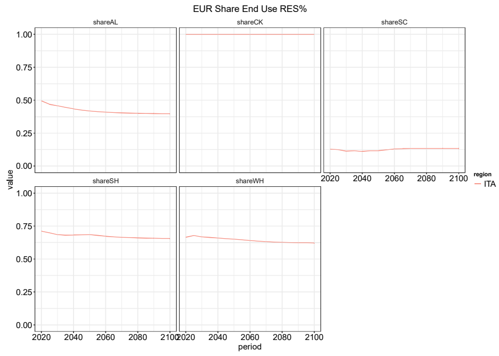

CHN Share End Use RES%
shareAL
shareCK
shareSC
shareSH
shareWH
region
CHN
value
period

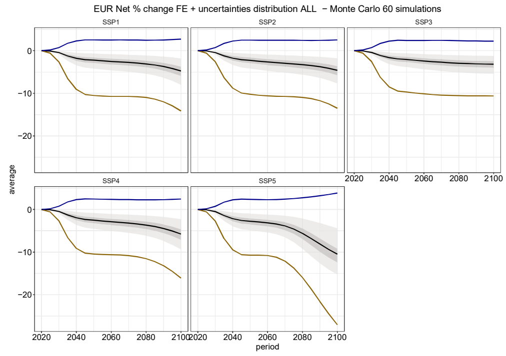

CHN Net % change FE + uncertainties distribution ALL − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

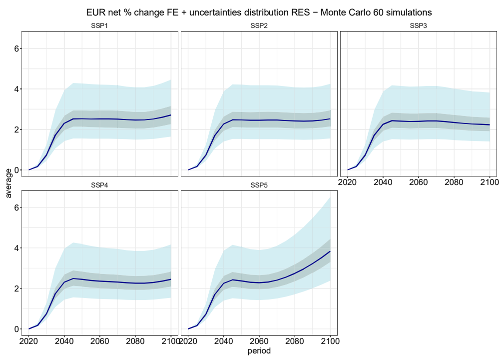

CHN net % change FE + uncertainties distribution RES − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

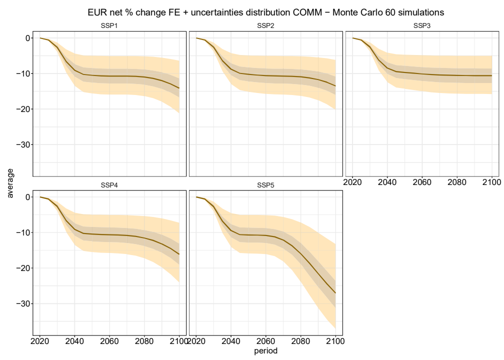

CHN net % change FE + uncertainties distribution COMM − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

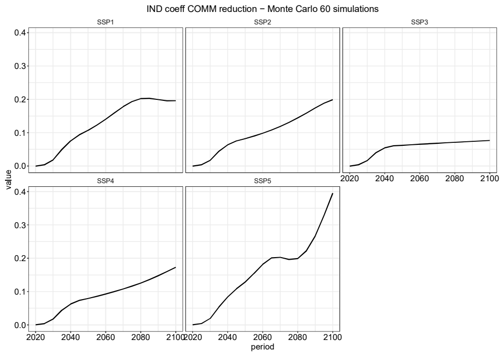

Fraction of EUR population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

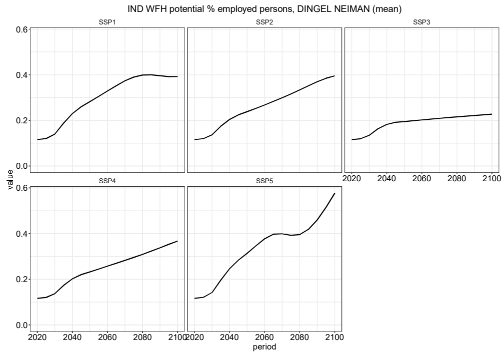

EUR Share End Use RES%
shareAL
shareCK
shareSC
shareSH
shareWH
region
ITA
value
period

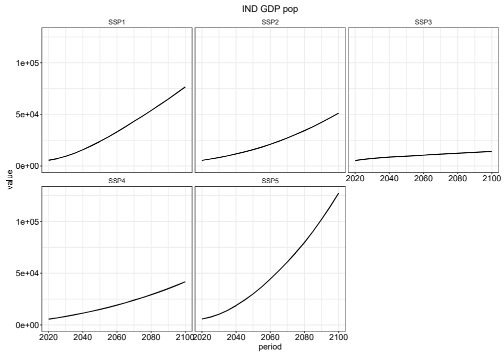

EUR Net % change FE + uncertainties distribution ALL − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

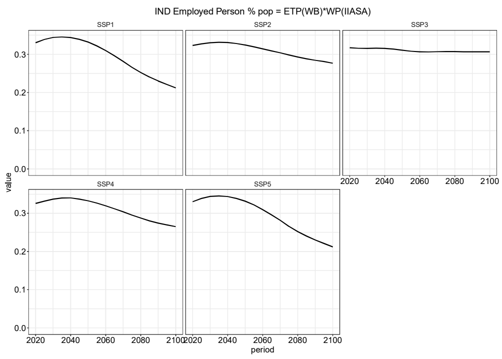

EUR net % change FE + uncertainties distribution RES − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

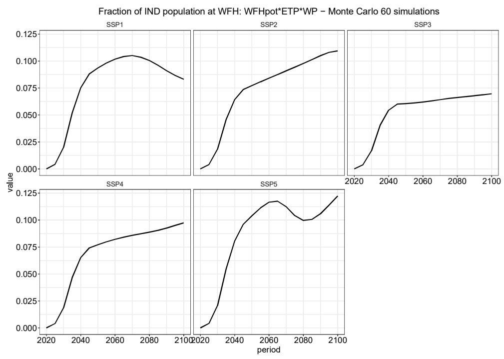

EUR net % change FE + uncertainties distribution COMM − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

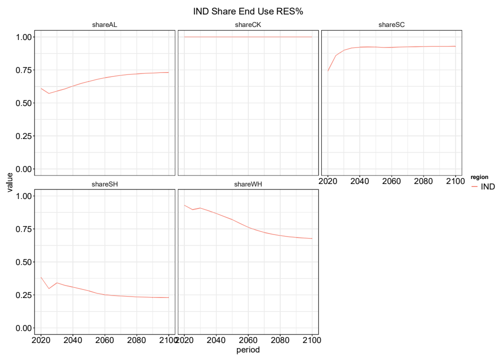

IND coeff COMM reduction − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

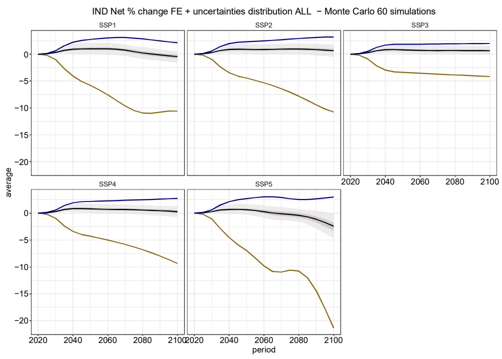

IND WFH potential % employed persons, DINGEL NEIMAN (mean)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

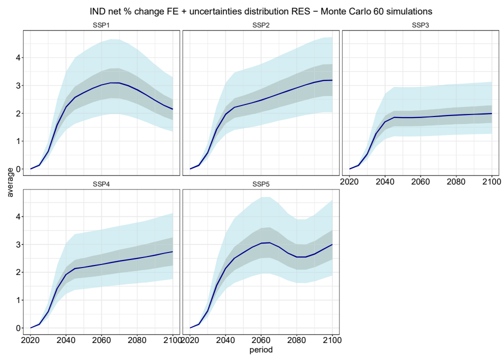

IND GDP pop
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

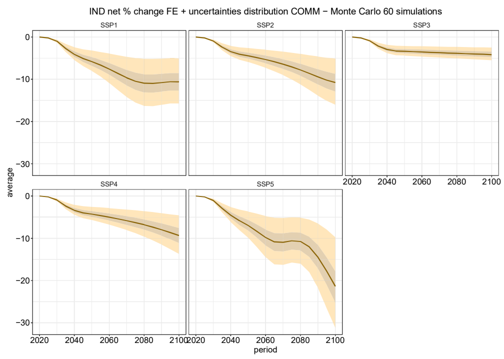

IND Employed Person % pop = ETP(WB)*WP(IIASA)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period


Fraction of IND population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

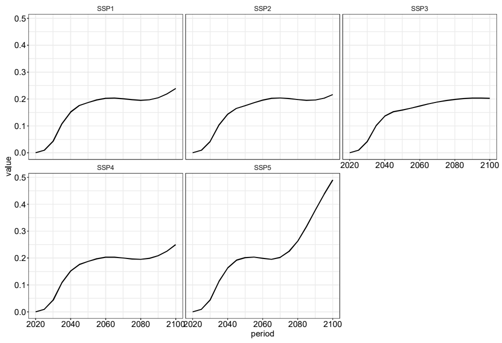

IND Share End Use RES%
shareAL
shareCK
shareSC
shareSH
shareWH
region
IND
value
period


IND Net % change FE + uncertainties distribution ALL − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

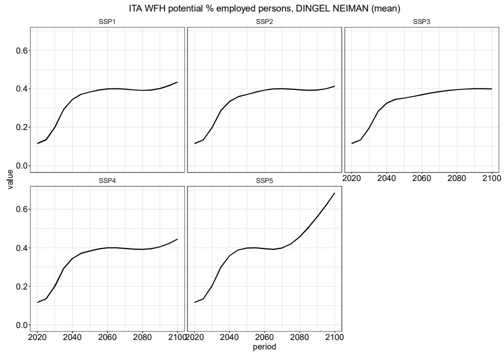

IND net % change FE + uncertainties distribution RES − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period


IND net % change FE + uncertainties distribution COMM − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

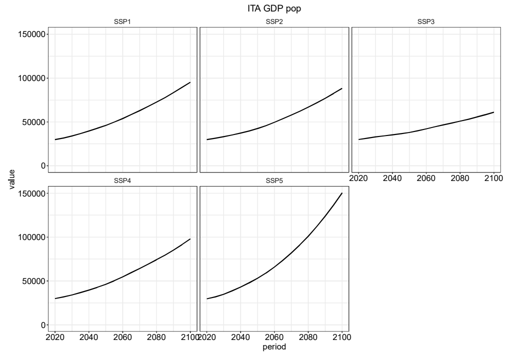
ITA coeff COMM reduction − Monte Carlo 60 simulations



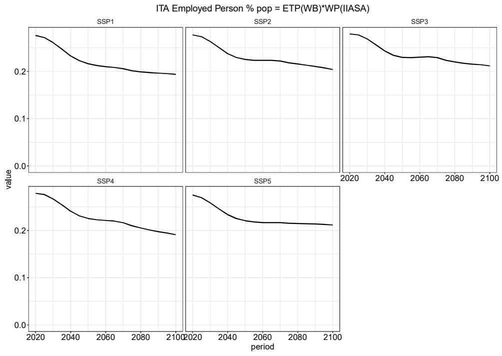
ITA WFH potential % employed persons, DINGEL NEIMAN (mean)



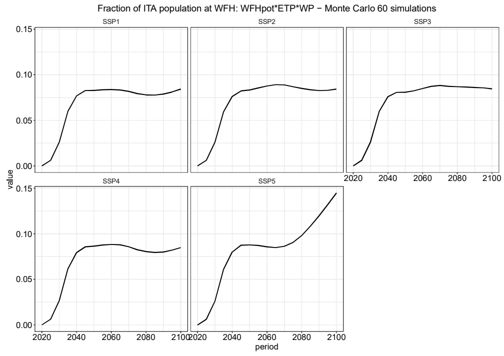
ITA GDP pop



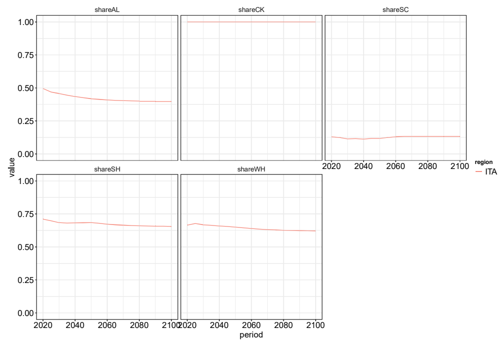
ITA Employed Person % pop = ETP(WB)*WP(IIASA)



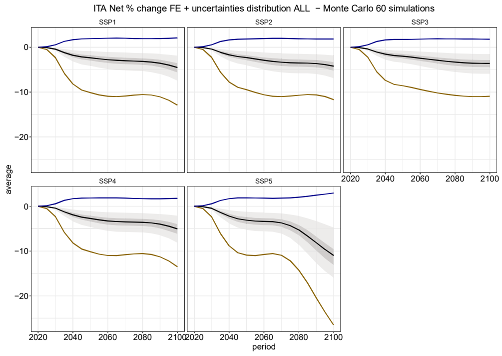
Fraction of ITA population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations



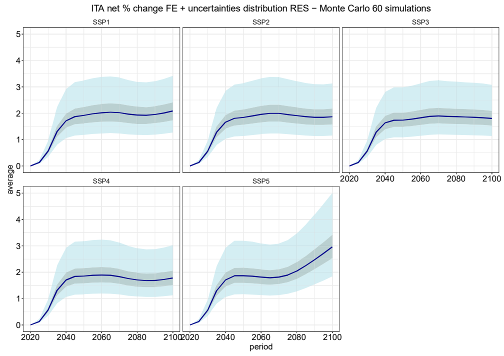
ITA Share End Use RES%



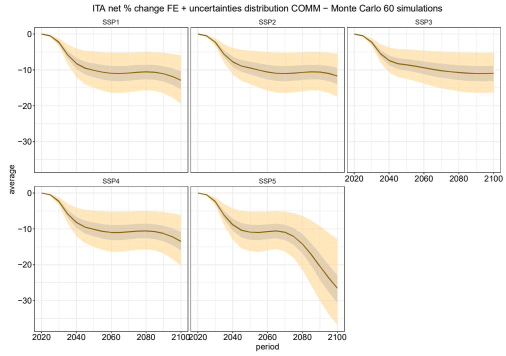
ITA Net % change FE + uncertainties distribution ALL − Monte Carlo 60 simulations

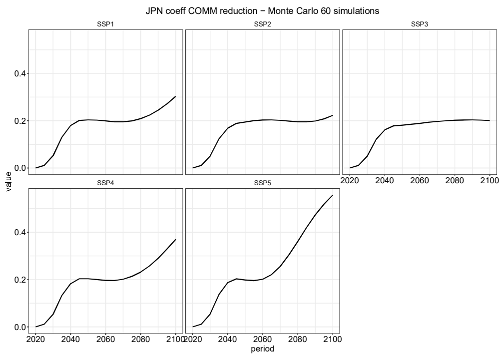


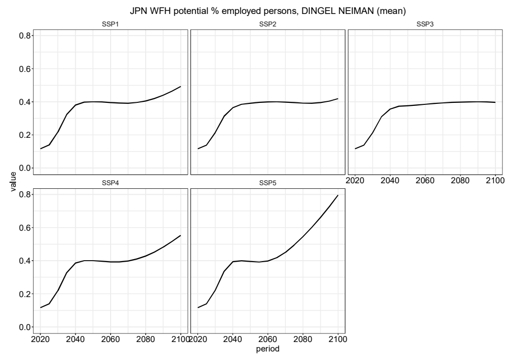
ITA net % change FE + uncertainties distribution RES − Monte Carlo 60 simulations

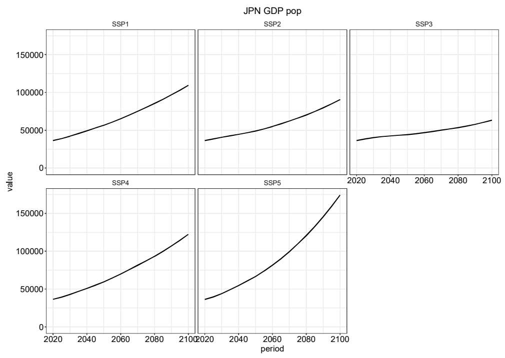


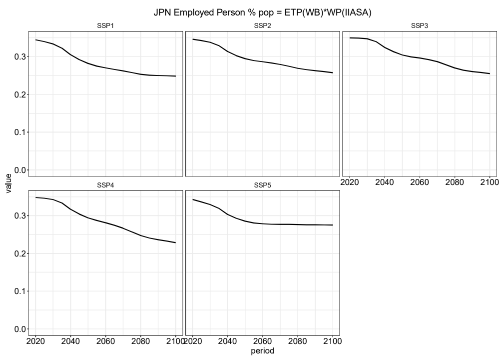
ITA net % change FE + uncertainties distribution COMM − Monte Carlo 60 simulations

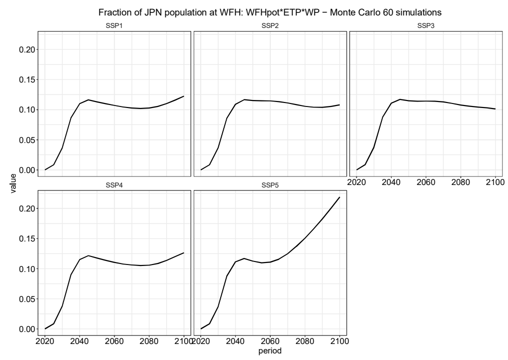


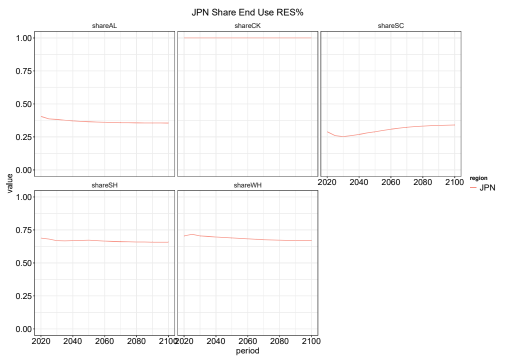

JPN coeff COMM reduction − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

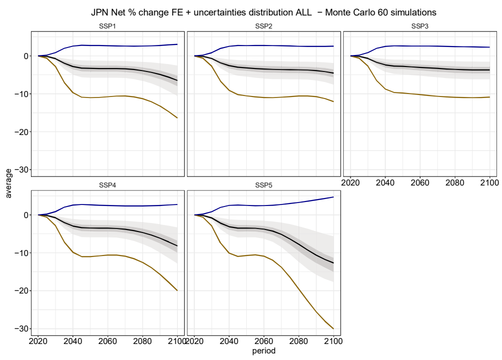

JPN WFH potential % employed persons, DINGEL NEIMAN (mean)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

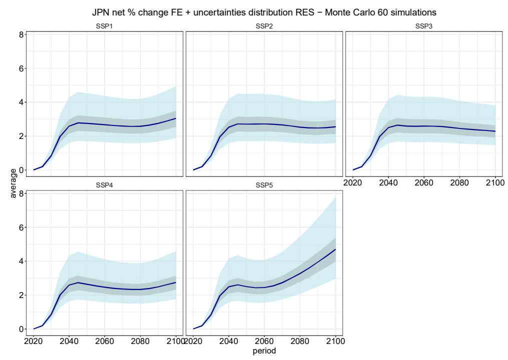

JPN GDP pop
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

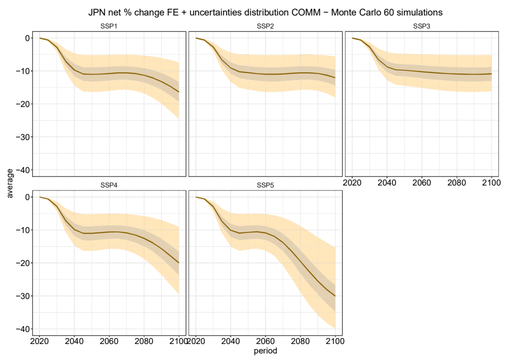

JPN Employed Person % pop = ETP(WB)*WP(IIASA)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

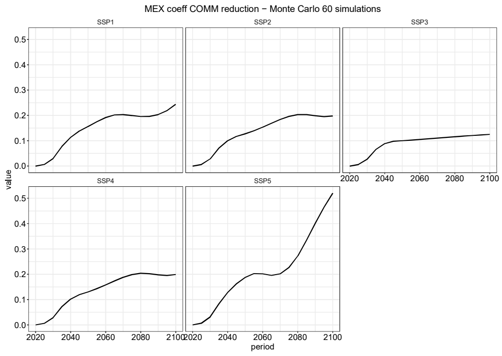

Fraction of JPN population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

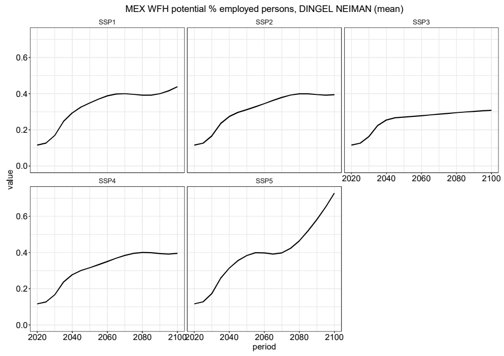

JPN Share End Use RES%
shareAL
shareCK
shareSC
shareSH
shareWH
region
JPN
value
period

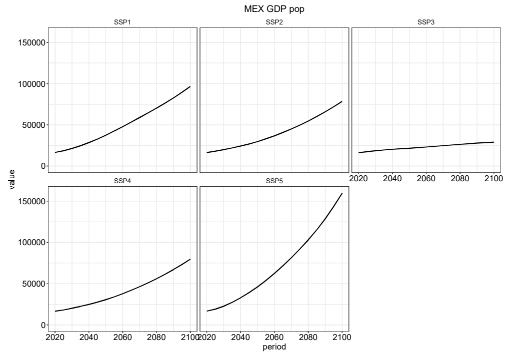

JPN Net % change FE + uncertainties distribution ALL − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

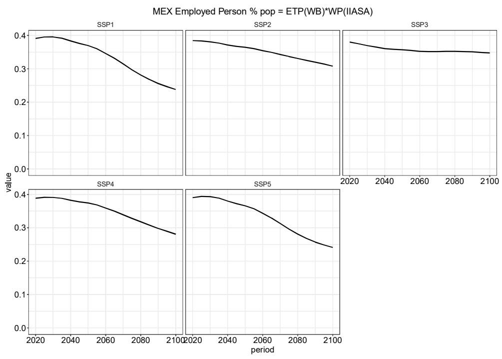

JPN net % change FE + uncertainties distribution RES − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

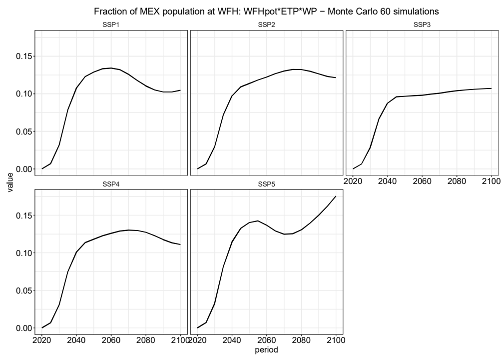

JPN net % change FE + uncertainties distribution COMM − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

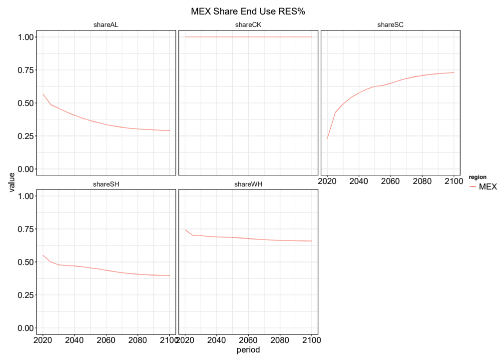

MEX coeff COMM reduction − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

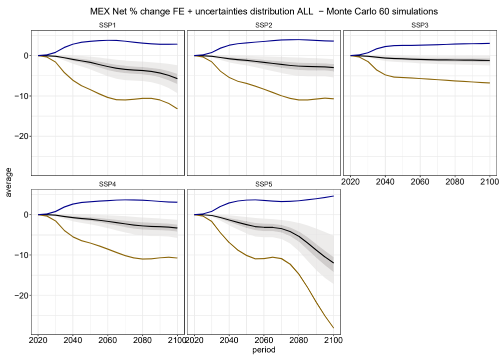

MEX WFH potential % employed persons, DINGEL NEIMAN (mean)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

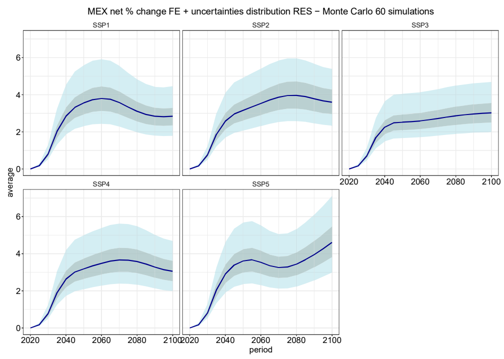

MEX GDP pop
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

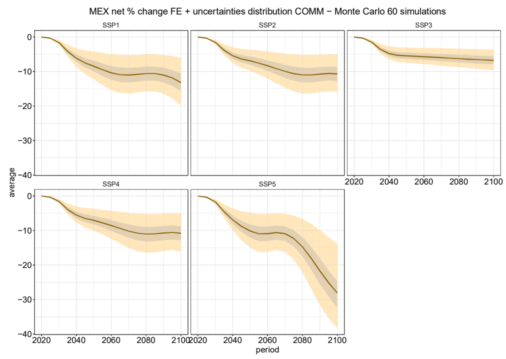

MEX Employed Person % pop = ETP(WB)*WP(IIASA)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

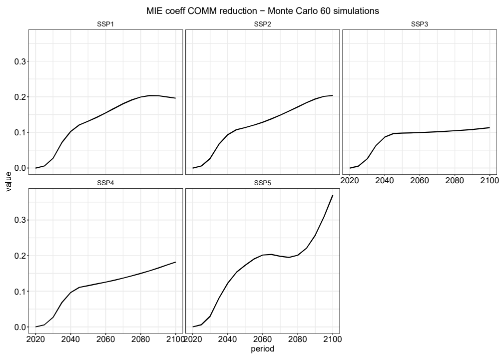

Fraction of MEX population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

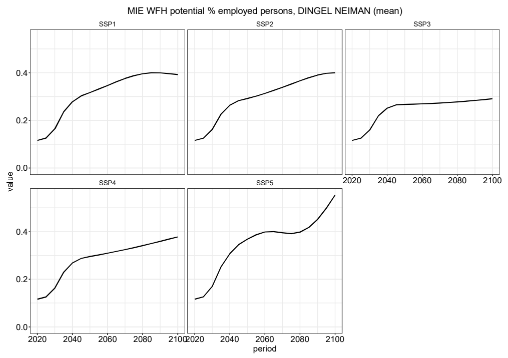

MEX Share End Use RES%
shareAL
shareCK
shareSC
shareSH
shareWH
region
MEX
value
period

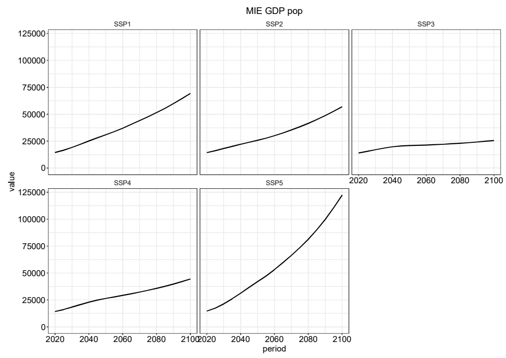

MEX Net % change FE + uncertainties distribution ALL − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

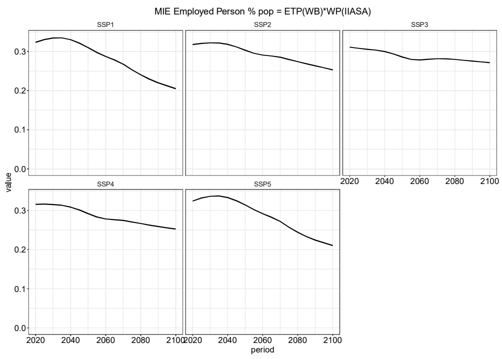

MEX net % change FE + uncertainties distribution RES − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

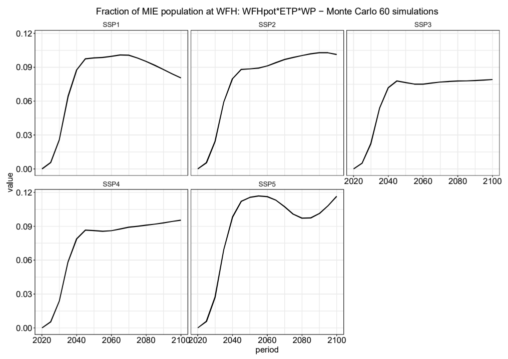

MEX net % change FE + uncertainties distribution COMM − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

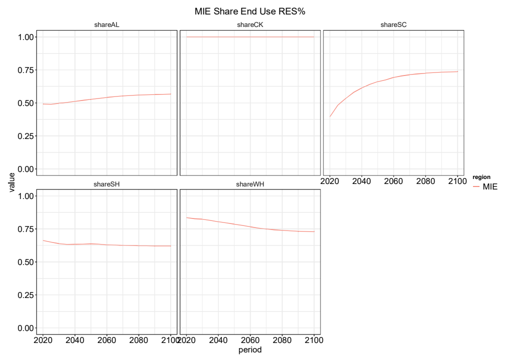

MIE coeff COMM reduction − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

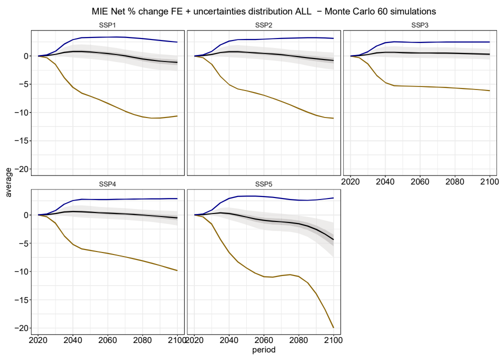

MIE WFH potential % employed persons, DINGEL NEIMAN (mean)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

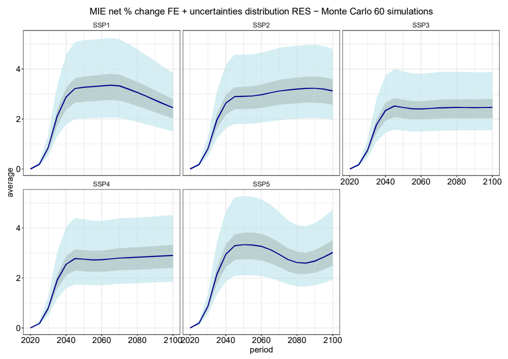

MIE GDP pop
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

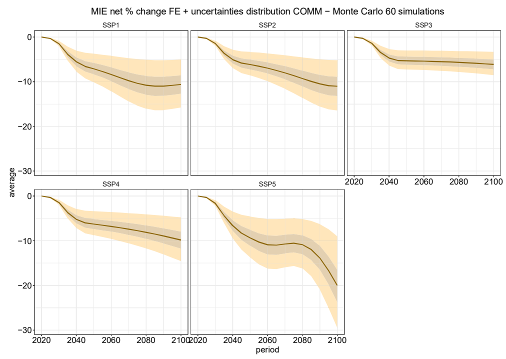

MIE Employed Person % pop = ETP(WB)*WP(IIASA)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period


Fraction of MIE population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

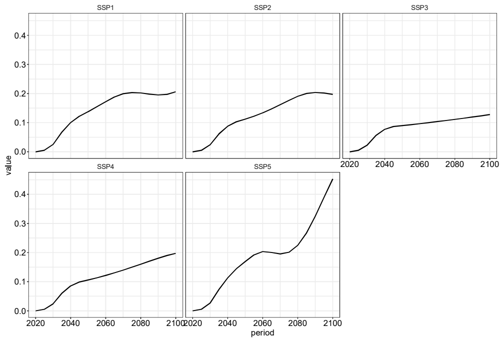

MIE Share End Use RES%
shareAL
shareCK
shareSC
shareSH
shareWH
region
MIE
value
period


MIE Net % change FE + uncertainties distribution ALL − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

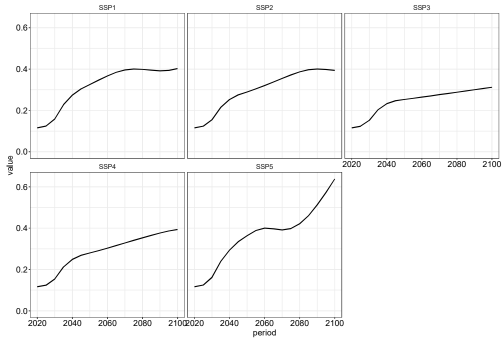

MIE net % change FE + uncertainties distribution RES − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period


MIE net % change FE + uncertainties distribution COMM − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

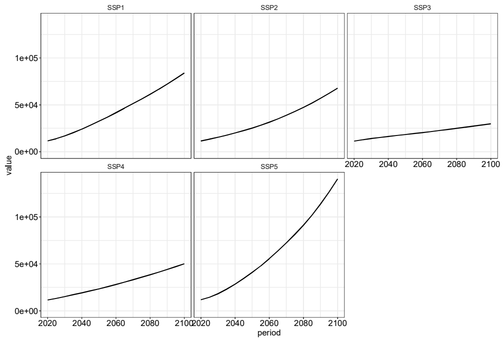
NCD coeff COMM reduction − Monte Carlo 60 simulations



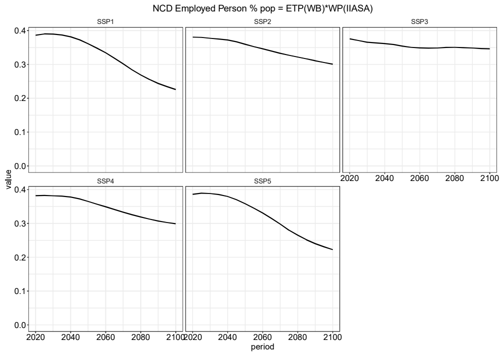
NCD WFH potential % employed persons, DINGEL NEIMAN (mean)



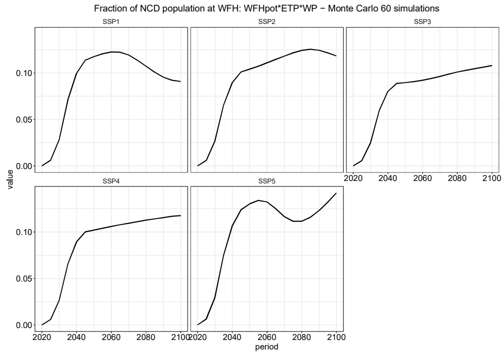
NCD GDP pop



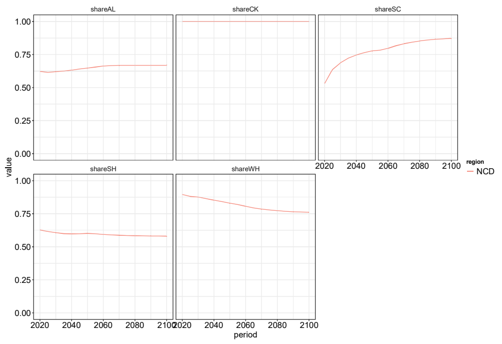
NCD Employed Person % pop = ETP(WB)*WP(IIASA)



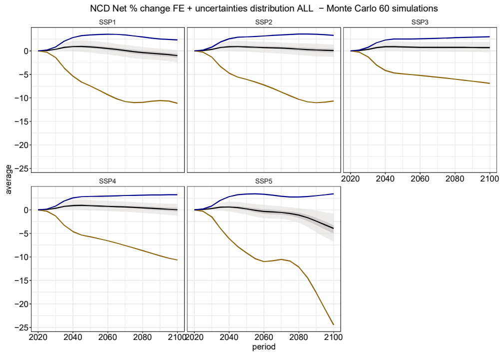
Fraction of NCD population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations



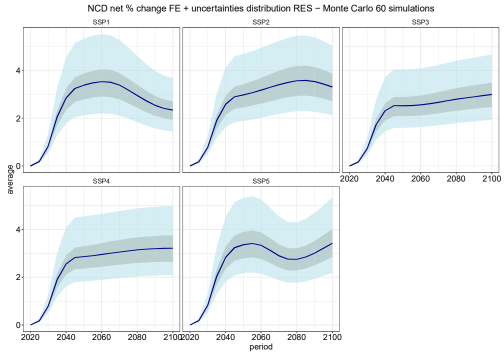
NCD Share End Use RES%



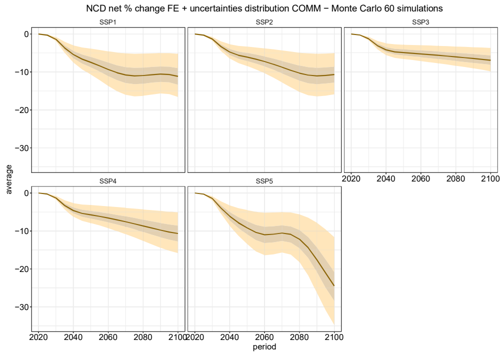
NCD Net % change FE + uncertainties distribution ALL − Monte Carlo 60 simulations

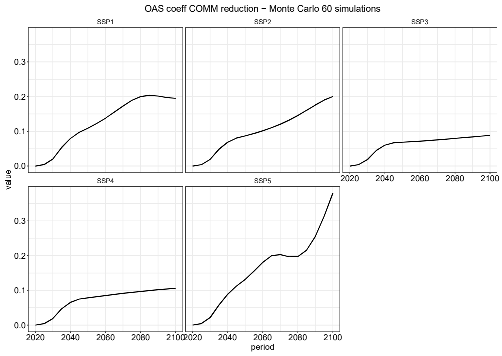


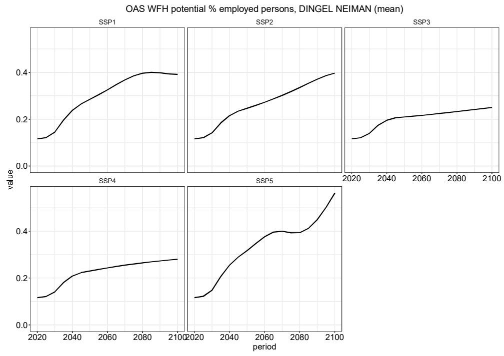
NCD net % change FE + uncertainties distribution RES − Monte Carlo 60 simulations

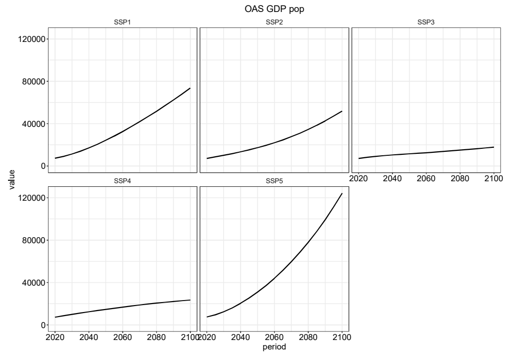


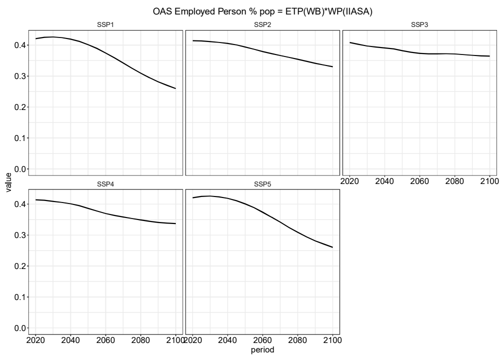
NCD net % change FE + uncertainties distribution COMM − Monte Carlo 60 simulations

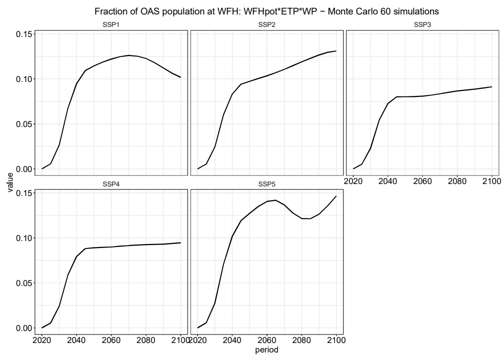


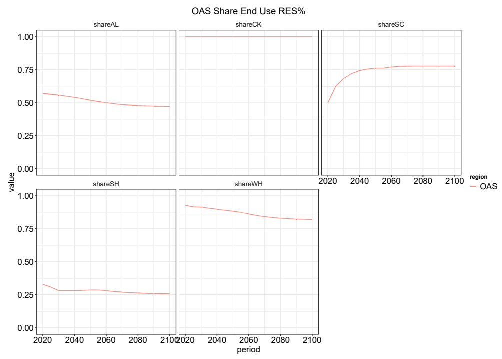

OAS coeff COMM reduction − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

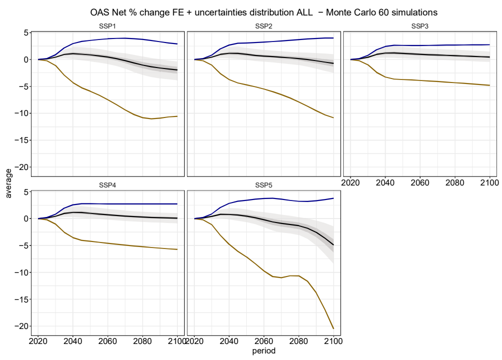

OAS WFH potential % employed persons, DINGEL NEIMAN (mean)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

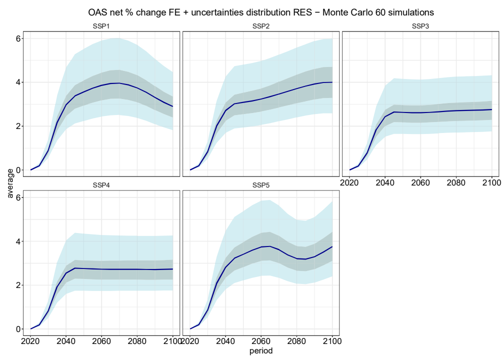

OAS GDP pop
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

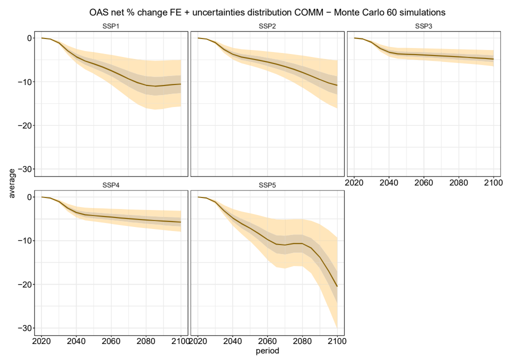

OAS Employed Person % pop = ETP(WB)*WP(IIASA)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

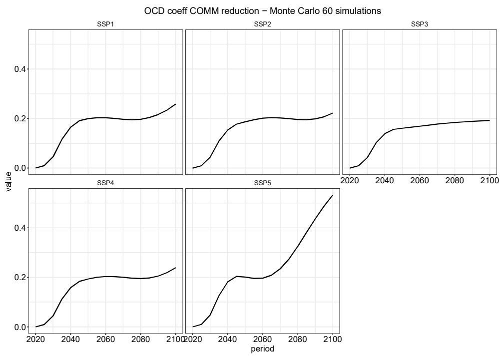

Fraction of OAS population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

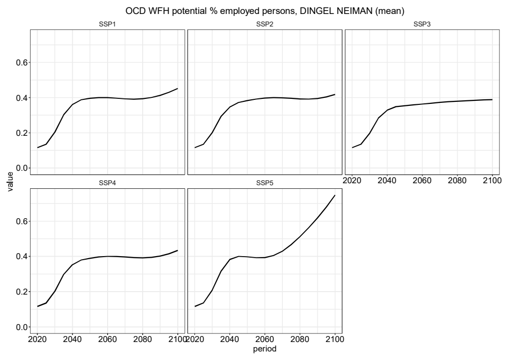

OAS Share End Use RES%
shareAL
shareCK
shareSC
shareSH
shareWH
value
period
region
OAS

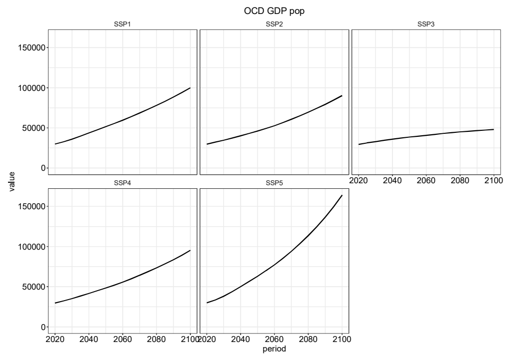

OAS Net % change FE + uncertainties distribution ALL − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

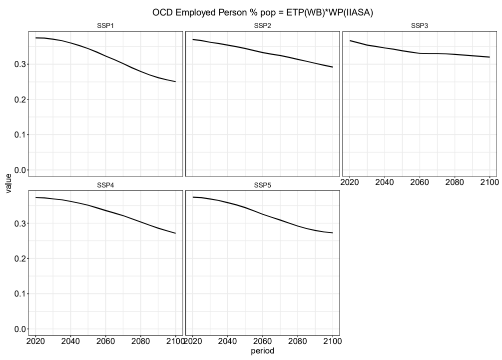

OAS net % change FE + uncertainties distribution RES − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

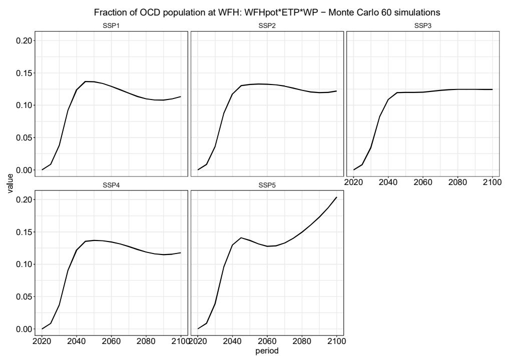

OAS net % change FE + uncertainties distribution COMM − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

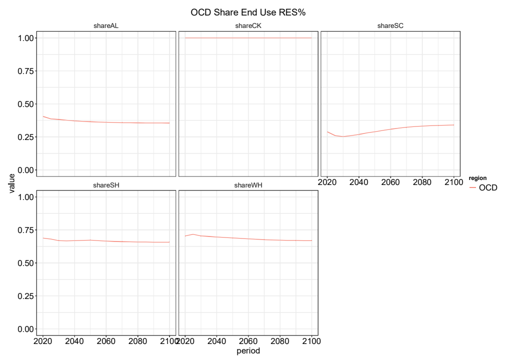

OCD coeff COMM reduction − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

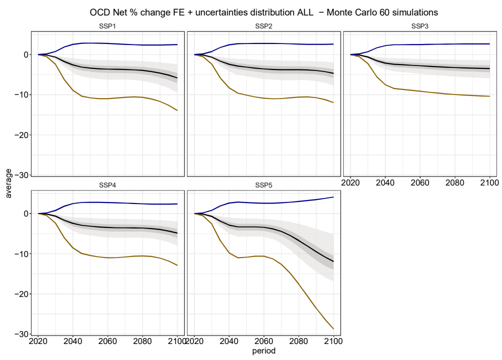

OCD WFH potential % employed persons, DINGEL NEIMAN (mean)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

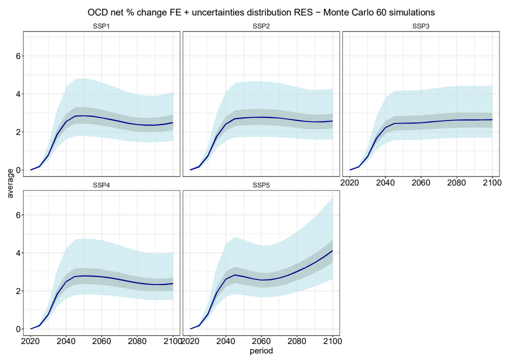

OCD GDP pop
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

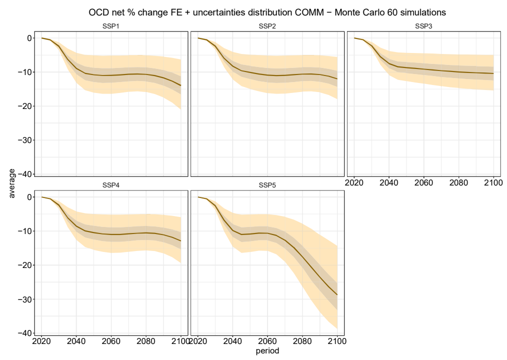

OCD Employed Person % pop = ETP(WB)*WP(IIASA)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period


Fraction of OCD population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

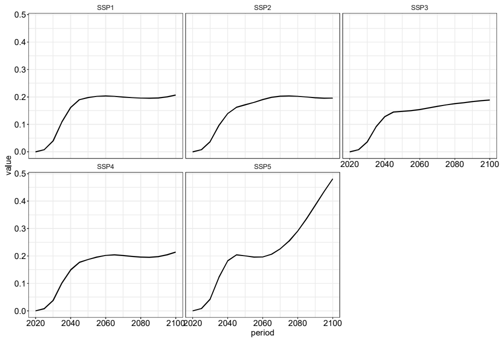

OCD Share End Use RES%
shareAL
shareCK
shareSC
shareSH
shareWH
region
OCD
value


OCD Net % change FE + uncertainties distribution ALL − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

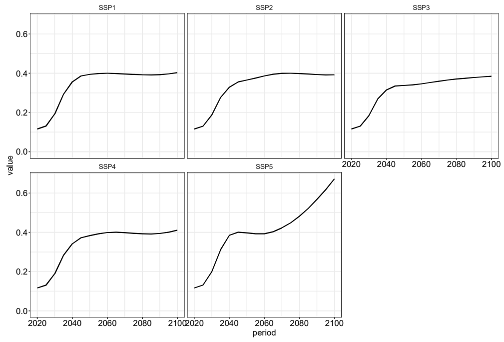

OCD net % change FE + uncertainties distribution RES − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period


OCD net % change FE + uncertainties distribution COMM − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

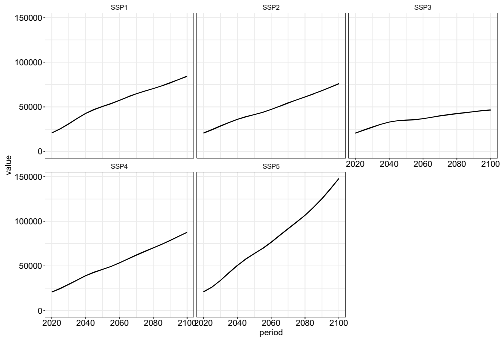
RUS coeff COMM reduction − Monte Carlo 60 simulations



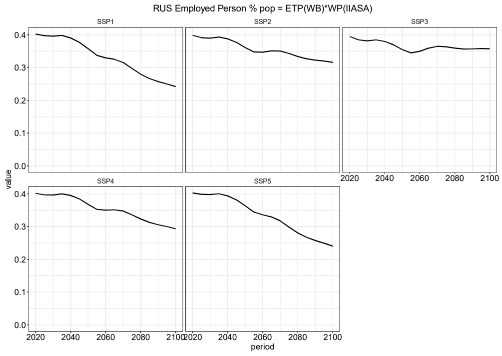
RUS WFH potential % employed persons, DINGEL NEIMAN (mean)



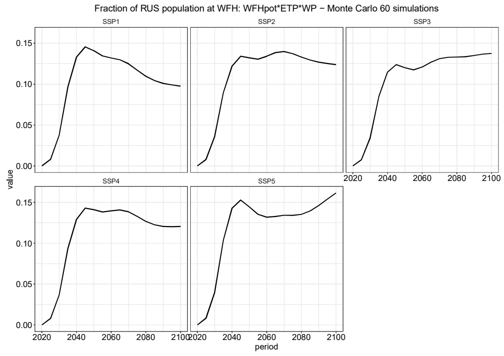
RUS GDP pop



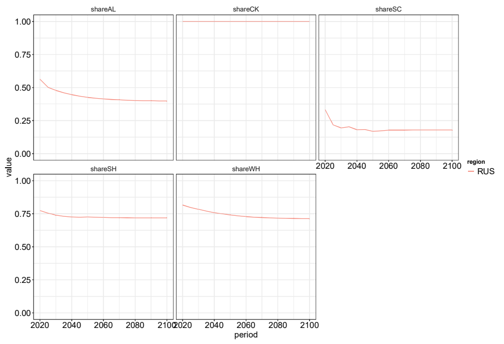
RUS Employed Person % pop = ETP(WB)*WP(IIASA)



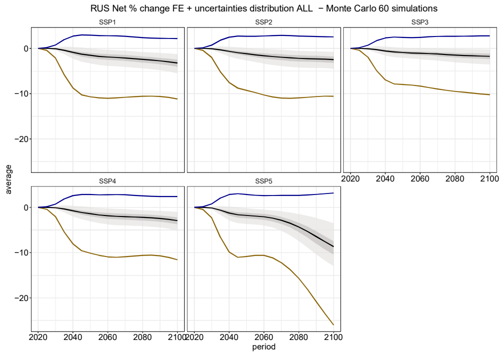
Fraction of RUS population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations



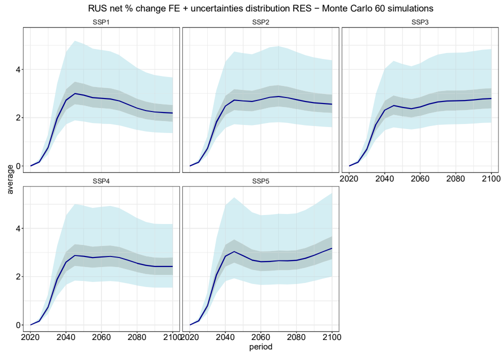
RUS Share End Use RES%



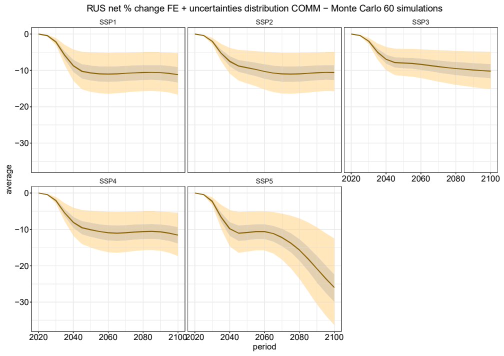
RUS Net % change FE + uncertainties distribution ALL − Monte Carlo 60 simulations



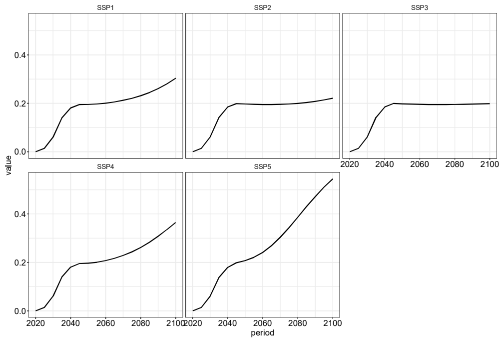
RUS net % change FE + uncertainties distribution RES − Monte Carlo 60 simulations



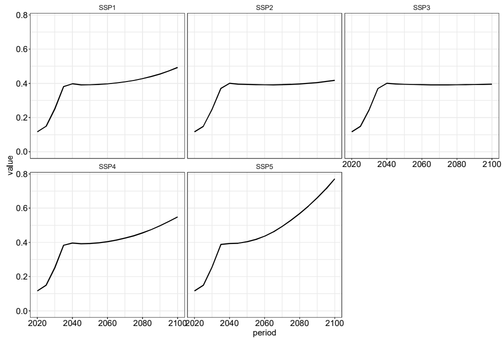
RUS net % change FE + uncertainties distribution COMM − Monte Carlo 60 simulations



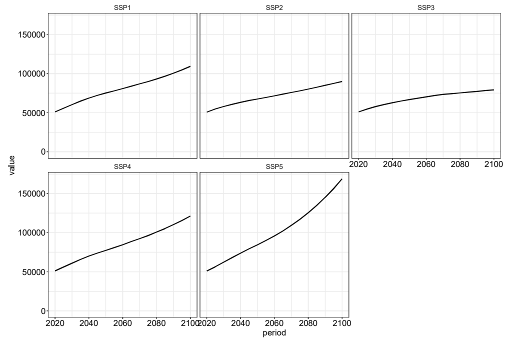
USA coeff COMM reduction − Monte Carlo 60 simulations



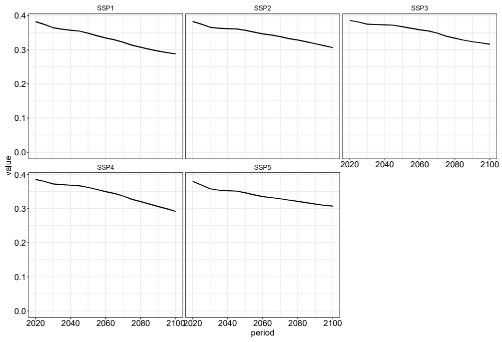
USA WFH potential % employed persons, DINGEL NEIMAN (mean)



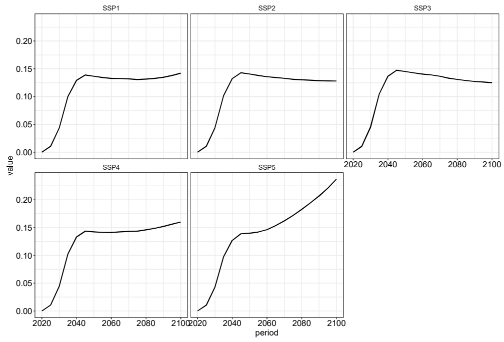
USA GDP pop



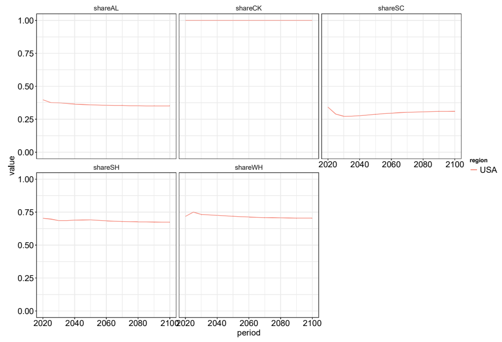
USA Employed Person % pop = ETP(WB)*WP(IIASA)



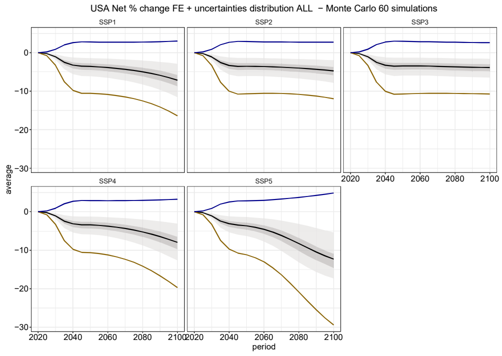
Fraction of USA population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations



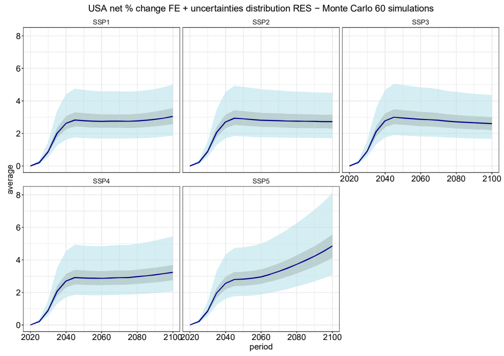
USA Share End Use RES%



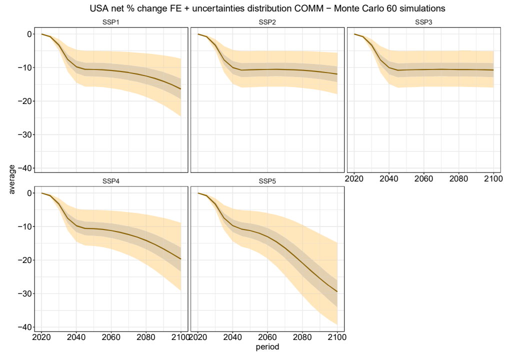
USA Net % change FE + uncertainties distribution ALL − Monte Carlo 60 simulations

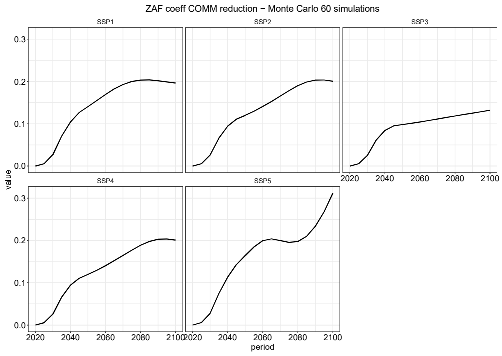


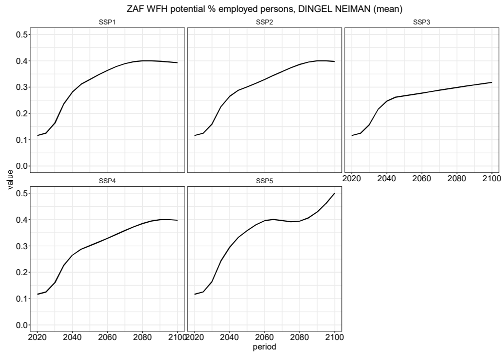
USA net % change FE + uncertainties distribution RES − Monte Carlo 60 simulations

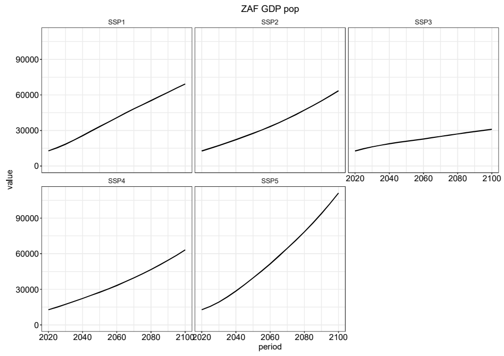


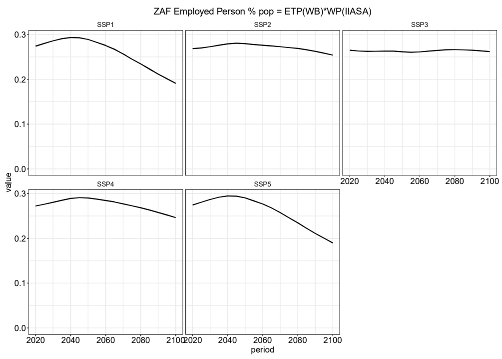
USA net % change FE + uncertainties distribution COMM − Monte Carlo 60 simulations

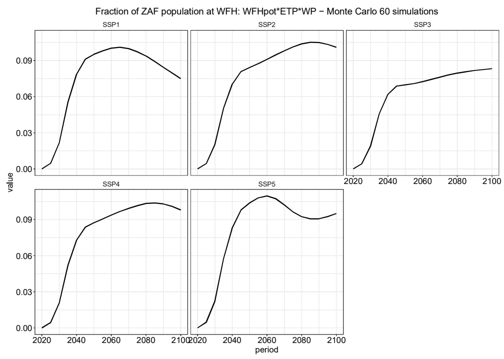


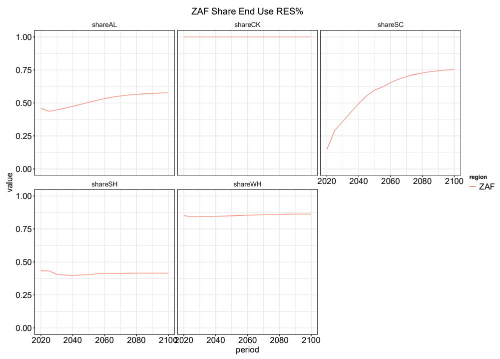

ZAF coeff COMM reduction − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

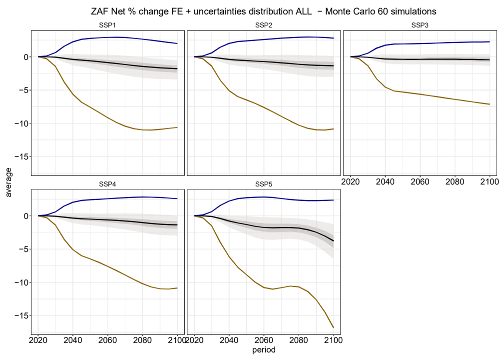

ZAF WFH potential % employed persons, DINGEL NEIMAN (mean)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

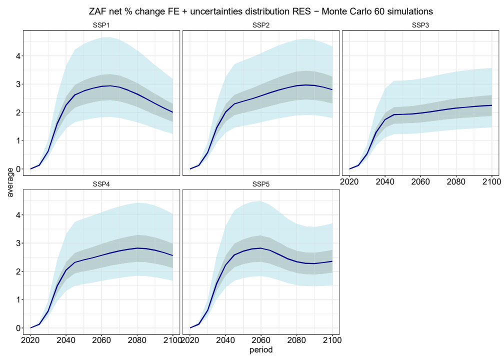

ZAF GDP pop
SSP1
SSP2
SSP3
SSP4
SSP5
value
period

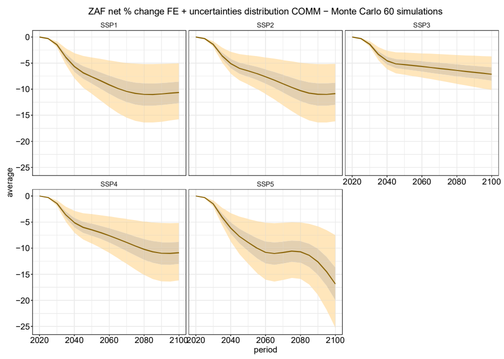

ZAF Employed Person % pop = ETP(WB)*WP(IIASA)
SSP1
SSP2
SSP3
SSP4
SSP5
value
period


Fraction of ZAF population at WFH: WFHpot*ETP*WP − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
value
period


ZAF Share End Use RES%
shareAL
shareCK
shareSC
shareSH
shareWH
region
ZAF
value
period


ZAF Net % change FE + uncertainties distribution ALL − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period


ZAF net % change FE + uncertainties distribution RES − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period


ZAF net % change FE + uncertainties distribution COMM − Monte Carlo 60 simulations
SSP1
SSP2
SSP3
SSP4
SSP5
average
period

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